Essays of Inter-firm Linkages and Return Predictability

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Declarations

This PhD thesis is based on the working papers below.

1. "Ownership Links and Return Predictability" (Lead author, co-authored with Angelica Gonzalez and Jun Tu).
2. "Mechanisms of The Return Predictability Along Ownership Links" (Lead author, co-authored with Angelica Gonzalez and Jun Tu).
3. "Return Predictability in The Labor Competition Network Based on Employee Satisfaction" (Lead author, co-authored with Xueying Bian and Jun Tu).

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The first and second papers have been presented at the conferences and universities listed below:

- **American Finance Association (AFA) 2019 Annual Meeting in Atlanta, USA.**
- Financial Management Association International 2018 Doctoral Student

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- European Financial Management Association 2018 Annual Meeting in Milan, Italy.
- Multinational Finance Society 2018 Annual Meeting in Budapest, Hungary.
- British Accounting and Finance Association 2018 Doctoral Colloquium in London, UK.
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- University of Edinburgh, Singapore Management University, University of Washington, Shanghai Jiao Tong University, Fudan University, University of Science and Technology of China, Sun Yat-sen University, Xiamen University, Shenzhen University, Southern University of Science and Technology, Southwestern University of Finance and Economics.

The third paper has been presented or will be presented at the universities below:

- National University of Singapore, Singapore Management University, Shanghai Jiao Tong University, Fudan University, McGill University.

The candidate confirms that he is the author of the three chapters. For each chapter, the candidate is responsible for completing the main components, such as the research proposal, literature review, data collection, statistical programming, and chapter writing. The three chapters made significant contributions and impressive implications to the literature of inter-firm linkages and return predictability. No part of this thesis has been submitted for any other degree or professional qualification.

The PhD candidate will become a tenure-track **Assistant Professor of Finance** at Shanghai Jiao Tong University from August 2019.

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List of Abbreviations

AG	Asset Growth
AMEX	American Stock Exchange
Alpha	Abnormal Return
BC	Best Companies of Employee Satisfaction
CAPM	Capital Asset Pricing Model
EMH	Efficient Market Hypothesis
ES	Employee Satisfaction
GP	Gross Profitability
Ind_mom	Industry Momentum
Ln(B/M)	The natural logarithm of Book-to-Market Ratio
Ln(Size)	The natural logarithm of Market Capitalization
Mom	Firm Momentum
NASDAQ	National Association of Securities Dealers Automated Quotations
Par	Parent firms
Sub	Subsidiaries
LSE	London Stock Exchange
NYSE	New York Stock Exchange
NYSE MKT	New York Stock Exchange Market

Abstract

In this thesis, I study whether stock returns are predictable. Specifically, I study whether the focal firm's[1] linked partners or linked peers can forecast its future returns. The literature of return predictability has found that a lot of forecasting variables, which are mainly constructed by the focal firm's own characteristics, can predict its future returns, but the predictive power from explicitly or implicitly linked firms is not fully explored and understood. The study of inter-firm return predictability has become an interesting and important research field, since it challenges current asset pricing theory and models.

In this thesis, my research questions are whether inter-firm return predictability exists in the ownership network (namely one new "explicit" network) and whether it exists in the similar employee satisfaction network (namely one new "implicit" network). The overall contribution of the thesis is to find new evidence of return predictability in the inter-firm networks. These new inter-firm return predictabilities are not only an interesting practical fact with implications for investing and hedging, but also have essential implications for new asset pricing factors.

[1] The focal firm means the firm that I mainly study and focus on.

In Chapter 2 and Chapter 3, I find the subsidiary-parent return predictability and parent-subsidiary return predictability in a global sample and different regional samples. In Chapter 4, I find that the returns of similar employee-satisfaction-linked firm peers have predictive power over focal firm returns. These results have important implications to call for a new asset pricing model that explicitly incorporates value-relevant information from various inter-firm networks.

Lay Summary

This PhD thesis consists of three empirical chapters, which investigates information diffusion and return predictability in corporate networks in terms of the ownership network and the employee satisfaction linkage. The chapter 2 and the chapter 3 can be read jointly. The chapter 4 can be read independently.

In the Chapter 2, I find the return predictability in the complex ownership network. The focal firm's returns can be forecasted by the lagged returns of their subsidiaries or parent firms. This return predictability pattern cannot be explained or subsumed by a series of firm characteristics and industry characteristics. This chapter finds the new evidence of return predictability in the explicit or concrete corporate network.

The Chapter 3 investigates possible mechanisms to explain the empirical findings of the Chapter 2. I find underlying mechanisms of the investors' limited attention, the limits to arbitrage, the opaque internal information of the conglomerate, and the information complexity, can explain the return predictability along ownership links. This chapter contributes new economic mechanisms to explain the return predictability in the corporate network.

In the Chapter 4, I study a novel inter-firm linkage, the employee satisfaction link. I find that lagged returns of employee satisfaction-linked firm peers can predict the returns of focal firms in the same labor competition network. Different with the product competition market, the common shocks to the labor competition market lead to the return predictability between employee satisfaction-linked firms. Different with the Chapter 2 and Chapter 3, this chapter provides the new evidence of return predictability in the implicit or soft corporate network.

CHAPTER 1 — Introduction

Modern finance began in the early 1970s. The Capital Asset Pricing Model (CAPM) and efficient market hypothesis (EMH) were established during that period. The Capital Asset Pricing Model (CAPM) was proposed by Sharpe (1964), Lintner (1965), and Mossin (1966). The CAPM measures market risk and return relationship, and explains why some stocks, strategies, portfolios and funds can gain more returns than others in the market. Basically, a high expected return involves high market risks. The efficient market hypothesis (EMH) was proposed by Malkiel and Fama (1970). The EMH claims that current stock prices instantaneously reflect all value-relevant information about the market and individual firms.

During the 1970s, academics believed that returns could not be forecasted. Firstly, stock returns are unpredictable. Stock prices are close to random walks over time. Efficient market hypothesis introduced analyses that tried to examine whether past stock prices, moving average line and trading volumes could predict future stock prices and help investors to earn an abnormal return above the market return. Any apparent stock return predictability can either be regarded as data snooping, which will be disappeared out of sample, or non-existent if I consider the transaction costs and trading constraints.

Secondly, bond returns are almost unpredictable. Bond returns come from the expectation model of term structure. If the short-term yields are less than the long-term yields, resulting in an upward sloping yield curve, this does not necessarily mean that the expected short-term bond returns are lower than the expected long-term bond returns. It is expected that the short-term interest rates will increase in the ensuing periods and investors can earn the same amounts by investing in either short-term or long-term bonds, if they invest in successive short-term bonds.

In addition, the FX rates are not predictable. If one foreign country has higher interest rates than the home country's interest rates, this does not necessarily indicate that abnormal returns can be earned by investing in that foreign country's bonds rather than the home country's bonds with a similar risk level, since its FX rate will be depreciated. Assuming the uncovered interest rate parity (UIP) relationship holds, once you exchange the foreign bonds for the currency of your home country, you are expected to earn the same amount of funds from trading in bonds of the foreign or home country.

Empirical evidence shows that professional fund managers are not able to outperform passively managed funds after correcting for market risk. Some managers can beat the market index in some years, but that is attributed to good luck. Others do worse than the market in any given year, and the outcome looks like bad luck. Managers cannot maintain the good performance until the next year, though the amount they earn is above the average in the current year. The evidence shows that the historical average of actively managed funds does roughly 1% worse than the indices portfolios.

These views indicate that asset markets are informationally efficient markets, which suggests that stock prices in the market reflect most fundamental value information. Competition leads to informational efficiency. It is not easy to make quick money, since the discovery of information about the traded assets' value is very competitive. The only way to earn more profits is by bearing more risks.

However, all of the above points have been replaced by a new series of return predictability research. Firstly, empirical evidence shows that stock returns were predictable through various financial ratios, such as the dividend-price and earnings-price ratios (Fama and French, 1989; Lewellen, 2004; Cochrane, 2011). Later, other variables were also shown to have the ability to forecast stock returns, such as the spread between long-term and short-term bond yields, the consumption-wealth ratio, macroeconomic variables, and corporate decision variables (Lettau and Ludvigson, 2001; Campbell and Thompson, 2008). Hou et al. (2018) summarize 452 forecasting variables that can explain and predict the cross-section of stock returns in the US sample.

The literature also covered returns on other asset classes, such as bonds, currencies, commodities, mutual funds, hedge funds, and real estate of many countries. First, bond returns are predictable. Although the expected model of term structure works in long periods, a soaring yield curve indicates that the expected returns of short-term bonds are lower than the expected returns of long-term bonds for the near future (Fama and French, 1989; Kirby, 1997; Ludvigson and Ng, 2009).

In addition, the FX returns are predictable. For example, if you purchase bonds in a country where interest rates are not usually higher than bond interest rates in the US, you can still earn more profits from investing that country’s bonds after converting the money to dollars (Bekaert and Hodrick, 1992). The trading strategy is called the carry trade (i.e., borrow in a low interest rate market and invest in a high interest rate market).

Finally, many funds can beat passive indices after correcting for market risks. Fund returns are predictable. For example, historically winning funds can continue to outperform previously losing funds in the future. The persistent skill is proven successfully in active management. However, the multifactor model explains why some funds can earn consistent profits by chasing stable factor-based investing 'styles' rather than persistent unique skills of stock selection (Ang et al., 2009; Ang, 2014).

In this thesis, I study whether stock returns are predictable. Specifically, I study whether the focal firm's[2] linked partners or linked peers can forecast its future returns. The literature of return predictability has found that a large number of forecasting variables (Hou et al., 2018), which are mainly constructed by the focal firm's own characteristics, can predict its future returns, but the predictive power from explicitly or implicitly linked firms is still not fully explored and understood. The study of inter-firm return predictability has become an interesting and important research field, since it challenges current asset pricing theory and models.

Cohen and Frazzini (2008) propose that firms are not independent but linked with each other. Some links are clear and contractual, but some links are implicit and less transparent. A firm's stock returns are not only influenced by the firm's own information, but also by the linked firms' value-relevant

[2] The focal firm means the firm that I mainly study and focus on.

information. The inter-firm return predictability is based on the use of the linked firms' lagged returns to forecast the future returns of focal firms. The gradual information diffusion (Hong and Stein, 1999) can explain the return predictability across firms. The gradual information diffusion model predicts that as private information travels across the population, pricing accuracy would improve, and asset prices would exhibit momentum as a result.

A large body of evidence confirms that the return predictability among firms has links to economics, technology, ownership and analysts, among others. Scholars have found that economically linked firms have return predictability. Cohen and Frazzini (2008) assess predictability between customers and suppliers. Cohen and Lou (2012) concentrate on the links between standalones and conglomerates. Huang (2015) and Finke and Weigert (2017) show that the foreign operation information of US firms and worldwide multinational firms can predict their returns. Cao et al. (2016) find that strategic alliance leads to return predictability. Parsons et al. (2019) find that some neighboring stocks can be predictors to forecast the future returns of focal returns. Lee et al. (2019) find technological innovation spillovers and predictable returns across firms. Ali and Hirshleifer (2019) find that stock returns between firms with shared analyst coverage could be predicted with each other.

An interesting question raised by this research is: why is there still return predictability over a long-time horizon (e.g., one month) even in a world where information transfers promptly through the existence of business networks? Although investors could conveniently receive a lot of financial information in this market of information explosion, investors still have limited cognitive abilities to deal with a wealth of information and may lack attention to essential value-relevant data that is not easy to observe. Here are two examples to highlight my points. Huberman and Regev (2001) study investors' inattention to salient news about a company. They found that the stock price of a company soared on the rerelease of information in the *New York Times* that was published in *Nature* five months earlier. Cohen and Frazzini (2008) study investors' inattention to the information of a firm's main customers. The firm (Callaway) announced a big drop in revenue on June 2001, but the stock price of the supplier (Coastcast) did not plunge until July 2001. The two examples indicate that investors may have longer responses to the public information. These delayed responses led to return predictability over a long-time horizon (e.g., one month).

In this thesis, the overriding research questions are whether inter-firm return predictability exists in the ownership network (namely one new "explicit" network) and the inter-firm return predictability in the similar employee satisfaction network (namely one new "implicit" network). The main contribution of the thesis is to find new evidence of return predictability in the inter-firm networks. These new inter-firm return predictabilities are not only an interesting practical fact with implications for investing and hedging, but also have essential implications for new asset pricing factors. These new inter-firm return predictabilities indicate that the stock market is not fully efficient or sometimes is inefficient due to investors' objective cognitive constraints (e.g., investors' limited attention) and investors' subjective biased beliefs (e.g., investors' sentiment force).

The Chapter 2 investigates the return predictability along ownership links. I study the subsidiary-parent and parent-subsidiary return predictabilities in a global sample and different regional samples. In addition, I study the sub-predictors by dividing the subsidiaries or parent firms into different sub-samples to predict the future returns of parent firms or subsidiaries.

There are two main contributions in the Chapter 2. Firstly, I find new inter-firm return predictabilities among ownership networks. The new predictors cannot be subsumed[3] by traditional predictors including the firm's characteristics and

[3] "subsumed" means "absorbed", "digested", or "explained". In the literature of return predictability, "subsume" or "subsumed" is widely used. For example, Finke and Weigert (2017,

industry momentum. In addition, I find that ownership-linked firm peers consisting of foreign firms, different industrial firms, minor firms, different name firms, or indirect firms can generate a greater predictive power over the returns of the focal firms. It indicates that investor responses are more seriously delayed when it comes to information from different countries, different industries, or uncertain sources. Finally, market-wide sentiment and attention can explain and provide a deeper understanding of the return predictability effect.

The Chapter 3 examines the mechanisms that can explain the return predictabilities along ownership links. The limits to arbitrage and the investors' limited attention are two behavioral mechanisms that can be used to explain the empirical findings of inter-firm return predictabilities (Cohen and Frazzini, 2008; Cohen and Lou, 2012; Huang, 2015; Cao et al., 2016; Finke and Weigert, 2017; Parsons et al., 2019; Lee et al., 2019; Ali and Hirshleifer, 2019). In this chapter, I further find that the opaque internal information of the conglomerate and the information complexity can explain the return predictability. These findings contribute knowledge about the new mechanisms to understand the inter-firm return predictability.

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p. 2215) state that "Hence, the Foreign_Info effect is different from the impact of other firm characteristics and is not *subsumed* by stock return reversal, momentum, and/or industry momentum." In Ali and Hirshleifer (2019), "subsume" or "subsumed" is widely used. One example is "We also find that past 12-month (skipping the most recent month) CF return *subsumes* the predictive power of past 12-month industry and geographic return variables".

The Chapter 4 studies the return predictability of employee satisfaction-linked firms through novel firm-ranking data based on employee satisfaction. I find that the returns of employee satisfaction-linked firms have predictive power over focal firm returns. A long-short strategy based on this effect yields a monthly Fama and French (2018) six-factor alpha of 135 basis points with 1% significance level. This effect is distinct from industry momentum and is not easily attributed to risk-based explanations. I find that investors' limited attention, limits to arbitrage, and information complexity may be mechanisms and reasons for the under-reaction to information about employee satisfaction-linked firms.

Given the obvious concrete links between firms, the current literature focus is probably not surprising. However, other potentially more subtle sources of information transfers may not be captured by concrete membership. Return predictability among firms that are linked by an alternative source or characteristic is less understood. In Chapter 4, I find that a type of intangible information, employee satisfaction, is a new linkage that enables the analysis of the information spillovers and return predictability across firms.

Overall, this thesis provides two new pieces of empirical evidence to prove inter-firm return predictability. The first is a concrete linkage, ownership links, and the other one is a soft linkage, employee satisfaction links. In addition, I develop new mechanisms to explain the return predictability across firms.

CHAPTER 2 — Ownership Links and Return Predictability

2.1 Introduction

La Porta et al. (1999) illustrate that public parent firms in Europe and Asia present a complex ownership structure, compared with Berle and Means (1932)'s image of a flat ownership of modern firms. There are plenty of potential benefits associated to this complex ownership structure, including the potential for operating and financing efficiently and a relatively low cost of monitoring. Investing in these complexed structured parent firms may present, however, tremendous challenges to some investors that have limited capacities and resources to deal with complicated value-relevant information. The presence of ownership structural horizontal complexities and vertical complexities, have the latent capacity to bring about market inefficiencies in the form of gradual, rather than immediate, information diffusion into stock prices (Hong and Stein, 2007; Duffie, 2010). It is possible to enable the information which derives from distant or poorly understood subsidiaries or parent firms to cause the slow information incorporation to parent firms or subsidiaries.

A parent firm, which controls its subsidiaries by ownership links, is exposed to unexpected stock price shocks because of stock price fluctuations of its financially linked subsidiaries. Particularly, a positive or negative shock to the main subsidiaries which are owned by their parent firm directly or indirectly is likely to rise or reduce the parent firm's future financial performance. There are at least two conceivable explanations to understand the return effect. Firstly, from an investment perspective, the partial equity ownership of subsidiaries can be regarded as an investment on behalf of their parent firm. If the stock price of subsidiaries increases, the parent firm's stock price should also increase contemporaneously to reflect appreciating assets. In other words, the equity in other firms represents an asset. If this asset increases in value, the market value of the parent firm will reflect it. Secondly, from an accounting perspective, since total or partial earnings of subsidiaries are included in their parent firm's total earnings in its consolidated financial statements,[4] changes in earnings of subsidiaries affect the stock prices of subsidiaries and their parent firm. If one parent firm has two subsidiaries, one subsidiary has positive information, but the other subsidiary has negative information, the total subsidiary information is difficult to analyze promptly by parent firm investors. Parent firm investors may have delayed responses to complicated information of subsidiaries.

[4] Consolidated financial statements refer to the combined financial statements of a parent firm and its subsidiaries.

The investors of subsidiaries may have delayed responses to the information of parent firms. Although the parent firm's earnings would not be included in the earnings of their subsidiaries, the parent firm has indirect influence on the performance of subsidiaries via capital, product, technology, and talent channels. In addition, from the viewpoint of the investors of listed subsidiaries, the parent firm's value-relevant information may be less informative since the performances of other subsidiaries may blur that of the listed subsidiaries. Hence, a more sophisticated analysis may be required to enable the understanding of how the consolidated information relates to the individual entities of the parent firm.

The literature in strategy, management, and marketing argues that the success of conglomerates depends on each entity's capability to transfer and manage the spillover of knowledge and resources (e.g., capital, markets, technologies, and talents) to other entities, and how each entity of the conglomerate effectively utilizes the said knowledge and resources. These specific transfers and spillovers include customer resource sharing, economic and strategic cooperation, technology transfer, manager appointment, talent allocation, brand redeployment, and business ethics influence. Valuable and rare knowledge and resource transfers affect subsidiary and parent firm performances in the long run and lead a conglomerate to a position of sustained competitive advantage.[5]

Cohen and Frazzini (2008) document return predictability across economically linked firms. They find that the lagged one-month return of main customers can predict the monthly returns of their suppliers. However, the mechanism behind the economic links is different from that of ownership links. Economic links refer to the firm's supply chain network, and reflect the firm's sales and operations activities, e.g., for firms with suppliers and/or customers. Ownership links refer to the company's ownership network, and reflect the company's investment and financing status, e.g., for firms with parent firms and/or subsidiaries. Their differences are also reflected in the changes in earnings on the financial statements. Customers' earnings are not part of the suppliers' total earnings in financial statements. Changes in the earnings of customers influence the sales of the suppliers and generate a new change in the earnings of the suppliers. However, the total or partial earnings of subsidiaries directly affect the value of the parent firm's total earnings in financial statements because of ownership links. According to the U.S. GAAP (Generally Accepted Accounting Principles) and IFRS (International Financial Reporting

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[5] See, for example, Barney (1991), Kogut and Zander (1993), Tsoukas (1996), Capron and Hulland (1999), Tsai (2001), Kor and Mahoney (2005), Berry et al. (2006), Dyer and Hatch (2006), Fang et al. (2007).

Standards),[6] parent firms must prepare annual and quarterly consolidated financial statements to report the financial wellbeing of both the parent firm and all of its subsidiaries.[7]

A large body of evidence confirms inter-firm return predictability among firms that have economic links. Scholars find that linked firms exist return predictability. Cohen and Frazzini (2008) assess predictability between customers and suppliers. Using a data set of the firms' main customers to identify a set of economically related firms, they show that the stock prices of suppliers do not incorporate news and information from their main customers, generating predictable stock returns. Cohen and Lou (2012) concentrate on the links between standalones and conglomerates. They find that when the same piece of information affects two groups of firms, one group does straightforward processing to incorporate information into stock prices, while the other group requires a more complicated analytical process to update the stock prices. Huang (2015) and Finke and Weigert (2017) show that the

[6] Since the end of the 1990s, U.S. GAAP (Generally Accepted Accounting Principles) and IFRS (International Financial Reporting Standards) are the two predominant accounting standards.

[7] Both U.S. GAAP and IFRS require parent firms to consolidate subsidiaries in which they own more than 50% of the voting rights. When it comes to associate entities in which the parent owns between 20% and 50% of voting rights, IFRS standards require the parent firm to consolidate the entity if the company is presumably de facto controlled by the parent firm, whereas U.S. GAAP requires the consolidation of these entities only if the parent firm demonstrates the exercise of a significant influence, namely "effective control", through board control or voting rights. In either case, consolidated financial statements use the equity approach.

information about the foreign operations of US firms and worldwide multinational firms can predict their returns. They both find that foreign operation information only dilutes the stock prices of multinational firms gradually. Cao et al. (2016) find that strategic alliance partners[8] lead to return predictability. However, return predictability among firms that are linked financially is less understood. Li et al. (2016) find that the lagged one-monthly returns of US local subsidiaries (parent firms) can predict next one-monthly returns of US parent firms (subsidiaries). They find that the subsidiary-to-parent return predictability is due to equity ownership, since the subsidiary-to-parent return predictability does not exist before the equity ownership is established. However, they find that the parent-to-subsidiary return predictability is unlikely to be caused by equity ownership; rather it is probably caused by the industry lead-lag effects. The investor's inattention and limits to arbitrage lead to the return effect. My study differs from theirs in other important dimensions. This chapter first provides comprehensive and thorough analysis, along with evidence to show global and regional sample results. In addition, I find a series of new predictors by sorting subsidiaries or parent firms into subsamples based on different categories. Finally, I find that market-wide

[8] Chan et al. (1997) document that strategic alliance partners are formed for several reasons including licensing, marketing or distribution, development or research, technology transfer or systems integration, or some combination of the above.

sentiment and attention can explain the return predictability along ownership links.

In this chapter, I study the return predictability between subsidiaries and parent firms and test a global sample including twenty-three developed markets. This broader international sample enables us to investigate whether the predictability effect is a common feature to markets globally. More importantly, I find that the subsamples of predictors have different predictive power based on different classifications. For instance, the return predictability effect differs between foreign and local predictors. Predictors that are in a different industry from the focal firm have a different return predictability effect from predictors that are in the same industry as the focal firm. Minor ownership predictors have a different return predictability effect from major ownership predictors.

I show that the information of subsidiaries has significant predictive ability for the parent firm's future stock returns on a global scale through different geographical subsamples. In the worldwide sample, from January 2008 to December 2017, the CAPM alpha is 1.19% in month t between parent firms' stocks with the highest monthly returns of ownership-weighted subsidiaries' portfolio at month $t-1$ and parent firms' stocks with the lowest monthly returns of ownership-weighted subsidiaries' portfolio at month $t-1$. After controlling for other risk factors, using the Fama and French six-factor model (Fama and French, 2018), I obtain 1.07% (t-statistic is 6.16) monthly abnormal returns of the value-weighted parent firms' portfolio. In addition, I find the monthly abnormal returns of the value-weighted portfolio through different geographical subsamples such as Asia-Pacific, Europe, and North America, which equal 1.03%, 1.47%, and 1.49%, respectively. I refer to this return predictability as "subsidiary momentum".

To test for the return predictability of a parent-subsidiary pair, I implement the following strategy. For each subsidiary i in month t, I calculate the control-weighted portfolio return of parent firms that own the subsidiary with at least 20% stakes. I then sort the subsidiaries into quintile portfolios using returns earned by a portfolio of their parent firms in the previous month. My results show that the lagged one-month return of the parent firms' portfolio has significant predictability for the subsidiaries' return in the next month. Specifically, a portfolio that goes long in the subsidiaries with a parent firms' portfolio that performed the best in the prior month and goes short in the subsidiaries with a parent firms' portfolio that performed the worst in the prior month yields a value-weighted CAPM alpha of 106 basis points (t = 3.79) and an value-weighted six-factor alpha of 94 basis points (t = 3.02) per month. I refer to this return predictability as "parent firm momentum".

Furthermore, lagged one-monthly ownership-linked firms' returns make a statistically and economically significant difference on future monthly returns of the focal firm in multivariate Fama-MacBeth stock-level regressions after controlling for assorted firm characteristics. The predictive relationship between past monthly returns of the predictor and one-month-ahead returns of the focal firm remains significant in the statistical and economic sense after controlling for the aforementioned characteristics of the firms.

Finally, anomalies can be driven by two common behavioral forces, namely 'subjective' sentiment, which represents investors' subjective biased beliefs, and 'objective' limited attention, which represents investors' objective cognitive constraints. Stambaugh et al. (2012) find that the returns of anomalies are higher in market-wide high sentiment periods and lower in market-wide low sentiment periods. Duan et al. (2018) find that the returns of anomalies are higher in market-wide low attention periods and lower in market-wide high attention periods. Therefore, I propose that the abnormal returns of anomalies are higher in a high sentiment and low attention period.

This chapter emphasizes the existing literature by documenting worldwide evidence of return predictability along ownership links. The contribution of this chapter is to find new evidence of inter-firm return predictability in the ownership networks. These new forecasting powers which use past subsidiaries' or parent firms' returns to predict future parent firms' or subsidiaries' returns not only constitute a thought-provoking empirical fact with implications for systematic investment and risk hedging, but also has important implications to call for a new asset pricing model that explicitly incorporates value-relevant information from ownership networks.

The remainder of the chapter proceeds as follows. Section 2.2 describes the data collection procedures and summary statistics, as well as explains the methodology of the empirical analysis. Section 2.3 presents the main results on portfolio sorts, cross-sectional regressions, and robustness tests. Section 2.4 shows the anomaly performance in different market-wide sentiment and attention periods. Section 2.5 studies the change status of ownership links and return predictability. Section 2.6 examines the impact of transaction costs on the profitability of the trading strategy. Section 2.7 comprises a brief but comprehensive conclusion.

2.2 Data and Methodology

2.2.1 Data

The sample covers parent firms and subsidiaries from twenty-three developed markets. The twenty-three developed markets are based on the MSCI world developed market index as of December 2017. The 23 developed markets include two North American markets (Canada and United States), sixteen European markets (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and United Kingdom), and five Asia-Pacific markets (Australia, Hong Kong, Japan, New Zealand, and Singapore). I collect price, volume, and return data for US firms from the Centre for Research in Security Prices (CRSP), and the same data for non-US firms from Thomson Reuter's Eikon. Institutional ownership data and analyst coverage for all firms in the sample are obtained from Thomson Reuters Institutional Holdings (13F) and Thomson Reuters I/B/E/S, respectively. I collect time-varying ownership links and shareholdings data from the FactSet database. I exclude stocks with prices below $5 to avoid market microstructure problems. I cover all industrial firms except firms in the financial sector[9] (with two-digit NAICS code = 52). The sample period is from January 2008 to December 2017 with a total of 120

[9] Financial firms are often excluded in empirical asset pricing literature (e.g., Finke and Weigert, 2017, Lee et al., 2019) since the characteristics of accounting variables of financial firms are very different from firms operating in the real economy.

months.[10] Like other international asset pricing literature, all stocks returns are denominated in USD.[11] Following Fama and French (2012), I use the one-month US T-bill rate for the USA and the remaining countries to calculate monthly excess returns.[12]

My aim is to investigate the return predictability from subsidiaries to their parent firms and the return predictability from parent firms to their subsidiaries. I have a reasonable cut-off of the ownership stake to study return effects. In La Porta et al. (2000), a large ownership stake is defined using a minimum of 10% in voting rights. Claessens et al. (2000) and Ginglinger et al. (2018) use a 20% cut-off to retain an ownership percentage equal to or more than 20%. Likewise, I also utilize 20 percent of ownership as a cut-off.[13] Since 2005, there has been a strong push for harmonization of accounting standards and principles with the mandatory adoption of International Financial Reporting Standards (IFRS) for public firms, which largely coincides with the U.S. GAAP. Both the U.S. GAAP and IFRS require parent firms to consolidate controlled subsidiaries. IFRS standards require the parent to consolidate the entity if

[10] I have only 10 years' historical ownership data due to the data availability.
[11] For example, Griffin (2002) and Fama and French (2012).
[12] My results are stable if I use local currency returns and work with raw returns rather than excess returns.
[13] I use the 10%, 15%, 25%, and 30% of ownership as a cut-off, but the results are not influential.

there is de facto control, which is interpreted as the ownership of a stake of 20% or more by the parent firm.

In order to test the return predictability for ten years, I collect ten annual time-varying ownership links. I use the ownership links in June of year $y-1$ to test the return predictability from January to December in year y.

2.2.2 Predictor – Subsidiaries' portfolio

The regressor of interest is the lagged one-monthly return of subsidiaries. It is referred to as $Sub_{i,t-1}$. In order to construct the predictor, I use the portfolio returns of subsidiaries, since one parent firm may have many subsidiaries. $Sub_{i,t-1}$ is constructed as the ownership-weighted[14] portfolio returns of subsidiaries:

$$Sub_{i,t-1} = \sum_{j} Own_{i,j,t-1} * Ret_{j,t-1},$$

$$Own_{i,j,t-1} = \frac{ShareHold_{\,i,j,t-1} * Size_{j,t-1}}{\sum_j ShareHold_{\,i,j,t-1} * Size_{j,t-1}},$$

[14] I compare different weighting approaches, including value-weighted, equal-weighted, and shareholding-weighted portfolios. But the ownership-weighted portfolio returns of subsidiaries have the largest predictive power to forecast parent firm's return based on the results of univariate portfolio sorts and cross-sectional regressions.

where $Sub_{i,t-1}$ denotes parent firm i's ownership-weighted portfolio returns of all subsidiaries, $Own_{i,j,t-1}$ is parent firm i's ownership stakes to subsidiary j in month $t-1$, $Ret_{j,t-1}$ is the subsidiary j's returns in month $t-1$, $ShareHold_{i,j,t-1}$ is parent firm i's shareholding percentages to the subsidiary j in month $t-1$, $Size_{j,t-1}$ is the market capitalization of subsidiary j in month $t-1$. For example, a parent firm (*P*) has two subsidiaries (*S1* and *S2*) in the first layer and *S1* has a subsidiary (*S11*) in the first layer. *S11* is a second-layer subsidiary to the parent firm (*P*). The market capitalizations of *P*, *S1*, *S2* and *S11* are 200 million, 100 million, 50 million, and 50 million, respectively. A parent firm *P* has shareholdings of 60% and 100% in *S1* and *S2*. *S1* has a shareholding of 50% in *S11*. In other words, *P* has a shareholding of 30% in *S11*. Thus, the predictor is:

$$Sub_{i,t-1} = \frac{60\% * 100 * Ret_{S1,t-1} + 100\% * 50 * Ret_{S2,t-1} + 30\% * 50 * Ret_{S11,t-1}}{60\% * 100 + 100\% * 50 + 30\% * 50}$$

2.2.3 Predictor - Parent firms' portfolio

The regressor of interest is the lagged one-monthly return of parent firms. It is referred to as $Par_{i,t-1}$. In order to construct the predictor, I use the portfolio returns of parent firms, since one subsidiary may have two or more parent firms. $Par_{i,t-1}$ is constructed as the control-weighted[15] portfolio return of parent firms:

$$Par_{i,t-1} = \sum_{j} Control_{i,j,t-1} * Ret_{j,t-1},$$

$$Control_{i,j,t-1} = \frac{ShareHold_{\ i,j,t-1}}{\sum_j ShareHold_{\ i,j,t-1}},$$

where $Par_{i,t-1}$ denotes subsidiary i's control-weighted portfolio return of all parent firms, $Control_{i,j,t-1}$ is subsidiary i's stake controlled by parent firm j in month $t-1$, $Ret_{j,t-1}$ is parent firm j's return in month $t-1$, $ShareHold_{\ i,j,t-1}$ is subsidiary i's shareholding percentages controlled by parent firm j in month $t-1$. For example, a subsidiary (*S*) has two parent firms (*P1* and *P2*) in the first layer and *P1* has a parent firm (*P11*) in the first layer. *P11* is a second-layer parent firm to the subsidiary (*S*). *P1* holds a 30% stake in *S*. *P2* holds a 20% stake in *S*. *P11* has a 50% shareholding in *P1*. In other words, *P11* has a shareholding of 15% in *S*. Thus, the predictor is exemplified below:

$$Par_{i,t-1} = \frac{30\% * Ret_{P1,t-1} + 20\% * Ret_{P2,t-1} + 15\% * Ret_{P11,t-1}}{30\% + 20\% + 15\%}$$

[15] I compare different weighting approaches, including value-weighted, and equal-weighted portfolios. But the control-weighted portfolio returns of parent firms have the largest predictive power to forecast subsidiary's return based on the results of univariate portfolio sorts and cross-sectional regressions.

2.2.4 Summary statistics

Table 2.1 shows the sample coverage and firm characteristics of the sample. In Panel A, I report the coverage of the sample. There are average 949 parent firms and 1702 subsidiaries each month. For each focal firm, it has 1.79 subsidiaries and 1.52 parent firms, respectively.

In Panel B, I summarize the firm characteristics. Parent firms' mean *Size* is 17.98 billion per month[16] and mean *Ln(B/M)* is -0.15 per month. Parent firms' mean Asset Growth (*AG*) and gross profitability (*GP*) are 0.14 and 0.39, respectively. Subsidiaries' mean *Size* is 2.86 billion per month and mean *Ln(B/M)* is -0.12 per month. Subsidiaries' mean Asset Growth (*AG*) and gross profitability (*GP*) are 0.19 and 0.43, respectively.

The parent firm's average size is 6.29 times greater than the subsidiary's average size in the global sample. This result is similar to statistics of Li et al. (2016). They find that the parent firm's average size is 6.54 times larger than the subsidiary's average size in the US sample.

[16] In the multi-layer ownership network, one parent firm may be not a top-layer parent firm (ultimate owner). For example, in the three-layer ownership network, one second-layer subsidiary is also a parent firm to the third-layer subsidiaries. Therefore, the parent firm's average size is not very big, since sometimes one subsidiary is also a parent firm in the multi-layer ownership network.

Table 2.1: Descriptive Statistics

This table presents summary statistics for parent firm variables and subsidiary variables used in the cross-sectional regressions. Financial firms (with two-digit NAICS code = 52) and stocks with price less than $5 at portfolio formation are excluded. Firm characteristics include firm's market capitalization (*Size)* in billions, book-to-market ratio (*Ln(B/M)*), asset growth (*AG*), gross profitability (*GP*). All variables are winsorized within each cross-section at 1% and 99% level. Panel A reports the sample description statistics. Panel B reports the descriptive statistics for firm characteristics. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A: Sample description					
Global	Mean	Sd	Min	Med	Max
# of parent firms	949	95	674	827	1212
# of subsidiaries	1702	186	1161	1589	2274
Average # subsidiaries per focal firm	1.79	1.14	1	2	7
Average # parent firms per focal firm	1.52	1.03	1	1	4

Panel B: Firm Characteristics					
Parent firm	Mean	Sd	Min	Med	Max
Size ($ bln)	17.98	31.21	2.37	17.10	47.92
Ln(B/M)	-0.15	0.14	-0.47	-0.18	0.26
AG	0.14	0.36	-0.60	0.08	8.83
GP	0.39	0.24	-0.84	0.37	1.29
Subsidiary					
Size ($ bln)	2.86	8.06	0.57	2.94	14.09
Ln(B/M)	-0.12	0.17	-0.43	-0.14	0.31
AG	0.19	0.36	0.00	0.03	1.37
GP	0.43	0.36	-0.41	0.40	1.21

2.3 Empirical Results

I next show the main results in the chapter. First, I report the empirical analysis of univariate portfolio sorts. Second, I show that return predictability is robust after controlling for a series of firm characteristics, industry momentum, and other inter-firm momentum. In addition, I show that return predictability is robust in different sub-periods and sub-samples. Finally, I report the performances of sub-predictors.

2.3.1 Univariate Portfolio Sorts

In this section, I report an empirical analysis of univariate portfolio sorts. Univariate portfolio sorts represent an intuitive and nonparametric way to test the cross-sectional variation of expected returns in response to a common predictor. They provide an essential cross-check for the cross-sectional regression tests, which I will present in the subsequent section.

In each month t, I rank focal firm returns based on the ranking of their ownership-linked firms' (subsidiaries' or parent firms') portfolio returns in month $t-1$. Then, I classify focal firm stocks into 5 quintiles.[17] Quintile 1

[17] Following the inter-firm return predictability literature (e.g., Cohen and Frazzini, 2008; Li et

includes focal firms with the lowest ownership-linked firms' portfolio returns over a lagged one-month period. Quintile 5 includes focal firms with the highest ownership-linked firms' portfolio returns over a lagged one-month period. Next, I report the value-weighted portfolio returns of Quintile 1 and Quintile 5 as well as the hedged portfolio returns of Quintile 5 minus Quintile 1 with a corresponding statistical significance level.[18] Univariate portfolio sorts are conducted in five regions: the Global sample, the Global sample excluding the USA, Asia-Pacific, Europe, and North America.[19] The global and regional pricing factors are procured from Kenneth French's webpage.[20] Finally, results are reported in Table 2.2. I show results of subsidiary-parent in Panel A-C and results of parent-subsidiary in Panel D-F.

The Capital Asset Pricing Model (CAPM)[21] is unable to explain satisfactorily the cross-sectional stock returns (Fama and French, 1992; Jagannathan and Wang, 1996). Therefore, I use Fama and French's (2015) five-factor model and Fama and French's (2018) six-factor model to examine cross-sectional

al., 2016; Finke and Weigert, 2017; Ali and Hirshleifer, 2019), I sort sample firms into quintiles. My results are also robust for decile portfolios.

18 In order to adjust for serial correlation in monthly stock returns, I use Newey and West (1987) standard errors in the statistical tests.

19 In order to show the universality and robustness of my strategy, I test my strategy in the global sample and four regional samples. Finke and Weigert (2017) also conduct univariate portfolio sorts in five different regions to show the robustness of their strategy.

20 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

21 This is the static CAPM.

variation in alphas, since the cross-sectional variation in expected returns can be captured by these hedged style factors (*SMB*, *HML*, *RMW*, *CMA*, and *MOM*). If the hedged portfolio returns have high correlation with one hedged style factor returns, those hedged portfolio returns are absorbed or subsumed by the hedged style factor returns. In other words, that hedged portfolio (strategy) does not contribute abnormal returns (alphas).

Capital Asset Pricing Model (CAPM):

$$RET_i - R_f = \alpha_0 + \beta_1(Mkt - R_f) + \varepsilon_i,$$

Fama and French (2015) five-factor model:

$$RET_i - R_f = \alpha_0 + \beta_1(Mkt - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \varepsilon_i,$$

Fama and French (2018) six-factor model:

$$RET_i - R_f = \alpha_0 + \beta_1(Mkt - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \beta_6 MOM + \varepsilon_i,$$

Where:

Following Fama and French (1993, 2015, 2018), I define these risk factors in the thesis. $Mkt - R_f$, *SMB*, *HML*, *RMW*, *CMA*, and *MOM* include all NYSE, AMEX, and NASDAQ firms. Fama and French (1993, 2015, 2018) use the six value-weight portfolios formed on size and book-to-market, the six value-weight portfolios formed on size and operating profitability, the six value-weight portfolios formed on size and investment, and the six value-weight portfolios formed on size and prior (2-12) returns to construct *SMB*, *HML*, *RMW*, *CMA,* and *MOM* factors.

$Mkt - R_f$: the excess return of the market. $Mkt - R_f$ is the value-weight return of all CRSP firms minus the one-month Treasury bill rate.

SMB (Small Minus Big): the nine small stock portfolios' average return minus the nine big stock portfolios' average return.

$$SMB_{\left(\frac{B}{M}\right)} = \frac{1}{3}(Small\,Value\ +\ Small\,Neutral\ +\ Small\,Growth)$$
$$-\frac{1}{3}(Big\,Value\ +\ Big\,Neutral\ +\ Big\,Growth).$$
$$SMB_{(OP)} = \frac{1}{3}(Small\,Robust\ +\ Small\,Neutral\ +\ Small\,Weak)$$
$$-\ \frac{1}{3}\ (Big\,Robust\ +\ Big\,Neutral\ +\ Big\,Weak).$$
$$SMB_{(INV)} = \frac{1}{3}(Small\,Conservative\ +\ Small\,Neutral\ +\ Small\,Aggressive)$$
$$-\ \frac{1}{3}\ (Big\,Conservative\ +\ Big\,Neutral\ +\ Big\,Aggressive).$$
$$SMB = \frac{1}{3}\left(SMB_{\left(\frac{B}{M}\right)} +\ SMB_{(OP)} +\ SMB_{(INV)}\right).$$

HML (High Minus Low): the two value portfolios' average return minus the two growth portfolios' average return.

$$HML = \frac{1}{2}\ (Small\ Value + Big\ Value) - \frac{1}{2}\ (Small\ Growth + Big\ Growth).$$

RMW (Robust Minus Weak): the two robust operating profitability portfolios' average return minus the two weak operating profitability portfolios' average return.

$$RMW = \frac{1}{2}\ (Small\ Robust + Big\ Robust) - \frac{1}{2}\ (Small\ Weak + Big\ Weak).$$

CMA (Conservative Minus Aggressive): the two conservative investment portfolios' average return minus the two aggressive investment portfolios' average return;

$$CMA = \frac{1}{2}\ (Small\ Conservative + Big\ Conservative) - \frac{1}{2}\ (Small\ Aggressive + Big\ Aggresive).$$

MOM: the two high prior return portfolios' average return minus the two low prior return portfolios' average return.

$$MOM = \frac{1}{2}\ (Small\ High + Big\ High) - \frac{1}{2}\ (Small\ Low + Big\ Low).$$

Table 2.2: Univariate Portfolio Sorts

This table reports the results of value-weighted univariate portfolio sorts. The results are shown for five regions: Global, Global ex USA, Asia-Pacific, Europe, and North America. I report univariate portfolio sorts of subsidiary-parent return predictability in Panel A-C. I report univariate portfolio sorts of parent-subsidiary return predictability in Panel D-F. Panel A and D present CAPM alphas for each quintile portfolio and the 5-1 difference portfolio. Panel B and E report risk-adjusted returns for each quintile portfolio and the 5-1 difference portfolio using a regional version of the Fama and French (2015) five-factor model. Panel C and F report risk-adjusted returns for each quintile portfolio and the 5-1 difference portfolio using a regional version of the Fama and French (2018) six-factor model. The risk factors are downloaded from the webpage of Kenneth French. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A: *Sub – Par*					
CAPM alphas	(1)	(2)	(3)	(4)	(5)
Value Weights	Global	Global ex USA	Asia-Pacific	Europe	North America
1 (Low)	-0.97***	-0.88***	-0.56***	-1.12***	-1.24***
2	-0.47***	-0.38**	-0.10	-0.60**	-0.15
3	-0.24*	-0.02	-0.06	-0.26	-0.23
4	-0.19	0.12	0.08	0.04	0.23
5 (High)	0.22*	0.33*	0.31*	0.42*	0.35*
5-1	1.19***	1.21***	0.87***	1.54***	1.58***
	(7.33)	(6.58)	(4.15)	(5.42)	(4.25)

Panel B: *Sub – Par*					
Five-factor alphas	(1)	(2)	(3)	(4)	(5)
Value Weights	Global	Global ex USA	Asia-Pacific	Europe	North America
1 (Low)	-0.96***	-0.83***	-0.60***	-1.30***	-1.23***
2	-0.41**	-0.30	0.05	-0.90***	-0.23
3	-0.18	0.07	-0.04	-0.63*	-0.33
4	-0.15	0.08	0.16	0.01	0.16
5 (High)	0.11*	0.27*	0.42*	0.20*	0.27*
5-1	1.07***	1.10***	1.02***	1.50***	1.50***
	(5.96)	(4.26)	(4.48)	(4.76)	(4.04)

Panel C: *Sub – Par*					
Six-factor alphas	(1)	(2)	(3)	(4)	(5)
Value Weights	Global	Global ex USA	Asia-Pacific	Europe	North America
1 (Low)	-0.96***	-0.83***	-0.64***	-1.28***	-1.20***
2	-0.41**	-0.30	0.03	-0.92***	-0.22
3	-0.18	0.06	-0.05	-0.65*	-0.35
4	-0.14	0.07	0.12	0.04	0.15
5 (High)	0.12*	0.27*	0.40*	0.19*	0.29*
5-1	1.07***	1.10***	1.03***	1.47***	1.49***
	(6.16)	(4.24)	(4.31)	(4.53)	(3.95)

Panel D: *Par – Sub*					
CAPM alphas	(1)	(2)	(3)	(4)	(5)

Value Weights	Global	Global ex USA	Asia-Pacific	Europe	North America
1 (Low)	-0.75***	-0.48*	-0.67*	-0.80*	-0.37*
2	-0.59**	-0.31	-0.52	0.20	-1.41***
3	-0.07	0.06	0.43	-0.49	-0.05
4	-0.05	-0.03	-0.09	0.46	0.04
5 (High)	0.31*	0.67**	0.81**	0.21	0.55*
5-1	1.06***	1.16***	1.48***	1.01**	0.92**
	(3.79)	(3.86)	(4.14)	(2.34)	(2.23)

Panel E: *Par – Sub*					
Five-factor alphas	(1)	(2)	(3)	(4)	(5)
Value Weights	Global	Global ex USA	Asia-Pacific	Europe	North America
1 (Low)	-0.80**	-0.50*	-0.60*	-1.09***	-0.32
2	-0.60*	-0.35	-0.56	0.07	-1.15**
3	-0.23	-0.21	0.50	-0.57	-0.10
4	-0.11	-0.23	-0.18	0.45	0.16
5 (High)	0.16	0.49*	1.03***	0.27	0.57*
5-1	0.96***	0.99**	1.63***	1.36***	0.89**
	(2.91)	(2.55)	(4.89)	(3.23)	(2.02)

Panel F: *Par – Sub*					
Six-factor alphas	(1)	(2)	(3)	(4)	(5)
Value Weights	Global	Global ex USA	Asia-Pacific	Europe	North America
1 (Low)	-0.80**	-0.50*	-0.68*	-1.19***	-0.40
2	-0.58*	-0.36	-0.63	0.08	-1.19**
3	-0.22	-0.22	0.46	-0.62	-0.16
4	-0.11	-0.23	-0.30	0.51	0.18
5 (High)	0.14	0.50*	1.14***	0.29	0.45*
5-1	0.94***	1.00***	1.82***	1.48***	0.85**
	(3.02)	(2.99)	(5.42)	(3.59)	(1.97)

Panel A demonstrates that monthly CAPM alphas of parent firm stocks with the highest lagged one-month returns for the subsidiaries' portfolio have obviously higher monthly CAPM alphas than those with the lowest lagged one-month returns for the subsidiaries' portfolio. The CAPM factor is market excess returns (market returns minus riskless rate). In the global samples, value-weighted parent firms' stocks in the highest quintile earn average monthly CAPM alphas of 0.22% with a significance level of 10%, but value-weighted parent firms' stocks in the lowest quintile earn average monthly CAPM alphas of -0.97% with a significance level of 1%. The return spread is 1.19% with a significance level of 1%. The value-weighted portfolio return spreads of the other region samples are 1.21% (Global ex USA), 0.87% (Asia-Pacific), 1.54% (Europe), and 1.58% (North America). All of these spreads in returns are statistically significant at 1%. The results of Panel A indicate that subsidiaries' returns have predictive power for future returns of focal firms in the global sample and in different geographical subsamples, since the CAPM fails to explain the return spreads.

Panel B reports the achievement of the Fama and French (2015) five-factor risk-adjusted returns for Quintile 1 and Quintile 5 and the hedged portfolio (Quintile 5 minus Quintile 1). The five factors are market excess returns, *SMB*, *HML*, *RMW*, and *CMA*. The value-weighted portfolio abnormal returns are 1.07% (Global), 1.10% (Global ex USA), 1.02% (Asia-Pacific), 1.50% (Europe), and 1.50% (North America). All of these spreads in returns are statistically significant at 1%. The results of Panel B indicate that subsidiaries' returns have predictive power for future returns of focal firms in the global sample and in different geographical subsamples, since the Fama and French (2015) five-factor model fails to explain the return spreads.

In Panel C, I use the Fama and French (2018) six-factor model to capture abnormal returns. The six factors are market excess returns, *SMB*, *HML*, *RMW*, *CMA*, and *MOM.* The value-weighted portfolio abnormal returns become 1.07% (Global), 1.10% (Global ex USA), 1.03% (Asia-Pacific), 1.47% (Europe), and 1.49% (North America). All of these spreads in returns are statistically significant at 1%. The results of Panel C indicate that subsidiaries' returns have predictive power for future returns of focal firms in the global sample and in different geographical subsamples, since the Fama and French (2018) six-factor model fails to explain the return spreads.

Panel D demonstrates that the monthly CAPM alphas of subsidiary stocks which have the highest lagged one-month return in the parent firm portfolio have obviously higher monthly CAPM alphas than those with the lowest lagged one-month return. The CAPM factor is market excess returns (market returns minus riskless rate). In the global samples, value-weighted subsidiary stocks in the highest quintile earn average monthly CAPM alphas of 0.31% with a significance level of 10%, but value-weighted subsidiary stocks in the lowest quintile earn average monthly CAPM alphas of -0.75% with a significance level of 1%. The return spread is 1.06% with a significance level of 1%. The value-weighted portfolio return spreads of the other region samples are 1.16% (Global ex USA), 1.48% (Asia-Pacific), 1.01% (Europe), and 0.92% (North America). All of these spreads in returns are statistically significant at the 5% level. The results of Panel D indicate that parent firms' returns have predictive power for future returns of focal firms in the global sample and in different geographical subsamples, since the CAPM fails to explain the return spreads.

Panel E reports the Fama and French (2015) five-factor risk-adjusted returns for Quintile 1 and Quintile 5 and the hedged portfolio (Quintile 5 minus Quintile 1). The five factors are market excess returns, *SMB*, *HML*, *RMW*, and *CMA.* I find that the spread returns of Quintile 5 minus Quintile 1 are statistically significant at the 5% level in five sample regions. Additionally, the value-weighted portfolio abnormal returns are 0.96% (Global), 0.99% (Global ex USA), 1.63% (Asia-Pacific), 1.36% (Europe), and 0.89% (North America). The results of Panel E indicate that parent firms' returns have predictive power for future returns of focal firms in the global sample and in different geographical subsamples, since the Fama and French (2015) five-factor model fails to explain the return spreads.

In Panel F, I use the Fama–French (2018) six-factor model to capture abnormal returns. The six factors are market excess returns, *SMB*, *HML*, *RMW*, *CMA*, and *MOM.* The value-weighted portfolio abnormal returns become 0.94% (Global), 1.00% (Global ex USA), 1.82% (Asia-Pacific), 1.48% (Europe), and 0.85% (North America). All of these spreads in returns are statistically significant at the 5% level. The results of Panel F indicate that parent firms' returns have predictive power for future returns of focal firms in the global sample and in different geographical subsamples, since the Fama and French (2018) six-factor model fails to explain the return spreads.

To briefly restate the main points, the results of Table 2.2 illustrate that lagged one-monthly returns of the ownership-linked firms' portfolio can forecast the returns of the focal firm in the next month. Moreover, the abnormal returns cannot be explained by implying asset pricing models, including global and regional Fama and French (2015, 2018) five-factor and six-factor models.

2.3.2 Cross-Sectional Regressions

In this section, I make use of the Fama and MacBeth (1973) regressions to analyze if the subsidiary-parent return predictability and parent-subsidiary return predictability remain robust after a set of risk factors and an array of different firm characteristics are regulated. Compared with other approaches (e.g., pooled OLS regressions) to deal with panel data, the Fama-MacBeth regressions take into account the cross-correlations and the serial correlation in the error term, so that the t-statistics are much more conservative (Choe et al., 2005). In addition, the Fama-MacBeth regressions are computationally simple to implement and are widely used in the literature of return predictability (Cochrane, 2005; Hou et al., 2018). The stock level's Fama-MacBeth regressions are made up of two steps. In the first step, I run the cross-sectional regression in each month as the following:

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,c,t} + \lambda_{2,d,t} + \lambda_{3,t}\, Sub_{i,t-1} + \lambda_{4,t}{}'\, X_{i,t-1} + \varepsilon_{i,t},$$

and

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,c,t} + \lambda_{2,d,t} + \lambda_{3,t}\, Par_{i,t-1} + \lambda_{4,t}{}'\, X_{i,t-1} + \varepsilon_{i,t},$$

where $RET_{i,t} - R_{f,t}$ is the excess return on the focal firm's stock i in month t; $\lambda_{0,t}$ denotes the intercept; $\lambda_{1,c,t}$ is a country-specific dummy variable which is equal to one if firm i is from country c and zero otherwise; $\lambda_{2,d,t}$ is an industry-specific dummy variable which is equal to one if firm i is from industry d and zero otherwise; $Sub_{i,t-1}$ is the lagged subsidiary stock return in month $t-1$; $Par_{i,t-1}$ is the lagged parent firm stock return in month $t-1$; $X_{i,t-1}$ represents a vector of controls, including $Ln(Size)$ the natural logarithm of the market capitalization (Banz, 1981), $Ln(B/M)$ the natural logarithm of book-to-market equity ratio (Basu, 1983), Mom the cumulative return of stock i from month $t-12$ to $t-2$ (Jegadeesh and Titman, 1993), $RET_{i,t-1}$ the stock return of focal firm i in month $t-1$ (Jegadeesh, 1990; Lo and MacKinlay, 1990), *Turnover* the number of shares traded divided by the number of shares outstanding during a day, averaged over the past twelve months (Rouwenhorst, 1999; Ibbotson et al., 2013), Ind_mom the value-weighted two-digit SIC industry return of the focal firm in month $t-1$ (Grinblatt and Moskowitz, 1999; Nijman et al., 2004), asset growth (AG) the year-over-year growth rate of total assets (Cooper et al., 2008), and gross profitability (GP) the revenue minus cost of goods sold scaled by assets (Novy-Marx, 2013).

The literature has found 452 forecasting variables to explain and predict the cross-sectional stock returns (Hou et al., 2018). However, I cannot use all of these forecasting variables as controls in my Fama-MacBeth regressions, since there is the serious overfitting problem (Han et al., 2018). I have to choose limited representative variables from different categories of variables. For example, the book/market ratio is a representative variable of the “value” variables, since Fama and French (1993) find that the book/market ratio can explain the value effect and absorb the predictive power of other “value” variables (e.g., earnings/price, dividend yield, and cash flow/price). Hou et al. (2018) divide 452 anomalies/forecasting variables into six categories (value, momentum, investment, profitability, intangibles, and trading frictions). Therefore, I select some representative forecasting variables from six categories as controls. These control variables are also widely used in Fama-MacBeth regressions in other inter-firm return predictability papers (e.g., Cohen and Lou, 2012; Lee et al., 2019; Ali and Hirshleifer, 2019).

After the first step, I obtain the time-series coefficients for each explanatory variable. The second step is to verify whether the average coefficient estimates are statistically different from zero. Bali et al. (2016) document steps to calculate standard errors by using the Newey-West (1987) method. In the second step, I firstly calculate the mean of time-series coefficients for each explanatory variable. Then I regress the time-series coefficients on a vector of ones to obtain the time-series residuals for each explanatory variable. Thirdly, I input the time-series residuals and a vector of ones to the Newey and West (1987) adjustment to compute the standard errors to deal with heteroscedasticity and autocorrelation. Finally, the t-statistics are calculated by the mean of time-series coefficients divided by the standard errors. Table 2.3 reports the mean of time-series coefficients and the corresponding t-statistics.

The standard errors are computed using the Newey and West (1987) adjustment with 6 lags. The choice of the lag length from 1 to 12 does not influence the significance of any of my tests. The monthly return predictability literature believes that residuals are heteroskedastic and/or autocorrelated within half a year or one year. For example, Cohen and Lou (2012) use Newey and West (1987) adjustment with 12 lags to compute the standard errors. Li et al. (2016) use Newey and West (1987) adjustment with 6 lags to compute the standard errors.

In addition, I study the delay in the information transmission process and capture this within a regression framework. Following Hou and Moskowitz (2005), I run the Fama-MacBeth (1973) regressions of the focal firm's excess returns on contemporaneous returns and four months of lagged returns on the subsidiaries' portfolio or parent firms' portfolio and a vector of control variables in the global sample and several regional samples. The regression can identify the delay in the information transmission process.

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,c,t} +$$

$$\lambda_{2,d,t} + \lambda_{3,t}\, Sub_{i,t} + \lambda_{4,t}\, Sub_{i,t-1} + \lambda_{5,t}\, Sub_{i,t-2} + \lambda_{6,t}\, Sub_{i,t-3} + \lambda_{7,t}\, Sub_{i,t-4} + \lambda_{8,t}{}'\, X_{i,t-1} + \varepsilon_{i,t},$$

and

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,c,t} +$$

$$\lambda_{2,d,t} + \lambda_{3,t}\, Par_{i,t} + \lambda_{4,t}\, Par_{i,t-1} + \lambda_{5,t}\, Par_{i,t-2} + \lambda_{6,t}\, Par_{i,t-3} + \lambda_{7,t}\, Par_{i,t-4} + \lambda_{8,t}{}'\, X_{i,t-1} + \varepsilon_{i,t},$$

where $RET_{i,t} - R_{f,t}$ is the excess return on the focal firm's stock i in month t; $\lambda_{0,t}$ denotes the intercept; $\lambda_{1,c,t}$ is a country-specific dummy variable which is equal to one if firm i is from country c and zero otherwise; $\lambda_{2,d,t}$ is an industry-specific dummy variable which is equal to one if firm i is from industry d and zero otherwise; $Sub_{i,t}$, $Sub_{i,t-1}$, $Sub_{i,t-2}$, $Sub_{i,t-3}$, and $Sub_{i,t-4}$ are the ownership-weighted subsidiaries' returns of focal firm i from month t to month $t-4$. $Par_{i,t}$, $Par_{i,t-1}$, $Par_{i,t-2}$, $Par_{i,t-3}$, and $Par_{i,t-4}$ are the control-weighted parent firms' returns of focal firm i from month t to month $t-4$; $X_{i,t-1}$ represents a vector of controls, including $Ln(Size)$ the natural logarithm of the market capitalization (Banz, 1981), $Ln(B/M)$ the natural logarithm of book-to-market equity ratio (Basu, 1983), Mom the cumulative return of stock i from month $t-12$ to $t-2$ (Jegadeesh and Titman, 1993), $RET_{i,t-1}$ the stock return of focal firm i in month $t-1$ (Jegadeesh, 1990; Lo and MacKinlay, 1990), *Turnover* the number of shares traded divided by the number of shares outstanding during a day, averaged over the past twelve months (Rouwenhorst, 1999; Ibbotson et al., 2013), Ind_mom the value-weighted two-digit SIC industry return of the focal firm in month $t-1$ (Grinblatt and Moskowitz, 1999; Nijman et al., 2004), asset growth (AG) the year-over-year growth rate of total assets (Cooper et al., 2008), and gross profitability (GP) the revenue minus cost of goods sold scaled by assets (Novy-Marx, 2013).

Table 2.3: Cross-Sectional Regressions

This table reports the results of cross-sectional Fama and MacBeth (1973) regressions. $RET_{i,t}$ is the excess return of focal firm i in month t. $Sub_{i,t}$, $Sub_{i,t-1}$, $Sub_{i,t-2}$, $Sub_{i,t-3}$, and $Sub_{i,t-4}$ are the ownership-weighted subsidiaries' returns of focal firm i from month t to month $t-4$. $Par_{i,t}$, $Par_{i,t-1}$, $Par_{i,t-2}$, $Par_{i,t-3}$, and $Par_{i,t-4}$ are the control-weighted parent firms' returns of focal firm i from month t to month $t-4$. Panel A reports the excess return of focal firm i, $RET_{i,t}$ is regressed on $Sub_{i,t-1}$ and a vector of control variables. Panel B reports the excess return of focal firm i, $RET_{i,t}$ is regressed on $Par_{i,t-1}$ and a vector of control variables. Panel C reports the excess return of focal firm i, $RET_{i,t}$ is regressed on contemporaneous and four months of lagged returns on the subsidiaries' portfolio. Panel D reports the excess return of focal firm i, $RET_{i,t}$ is regressed on contemporaneous and four months of lagged returns on the parent firms' portfolio. Control variables include *Ln(Size)* (the log market capitalization at the end of December of previous calendar year), *Ln(B/M)* (the log book-to-market ratio at the end of December of previous calendar year), $RET_{i,t-1}$ (the lagged one-monthly return of the focal firm), *Mom* (the lagged focal firm's cumulative returns from month $t-12$ to month $t-2$), *Turnover* (the number of stocks traded divided by the number of stocks outstanding during a day, averaged over the past twelve months), Ind_mom

(the lagged one-monthly domestic industry return), *AG* (asset growth, the year-over-year growth rate of total asset), and *GP* (gross profitability, the revenue minus cost of goods sold scaled by assets). T-statistics are shown in parentheses and calculated by using the Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A: *Sub-Par*	(1)	(2)	(3)	(4)	(5)
*100	Global	Global ex USA	Asia-Pacific	Europe	North America
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Sub_{i,t-1}$	6.32***	4.86**	2.06***	4.63**	4.15***
	(3.35)	(2.33)	(5.92)	(2.02)	(3.30)
Ln(Size)	-0.10*	-0.13*	-0.07**	-0.06	0.05
	(-1.75)	(-1.81)	(-2.37)	(-1.21)	(0.86)
Ln(B/M)	0.23**	0.50***	0.44**	0.43***	-0.17
	(2.11)	(4.04)	(2.32)	(3.26)	(-0.36)
$RET_{i,t-1}$	-6.73***	-4.19***	-1.41	-6.38**	-9.96***
	(-3.52)	(-3.13)	(-1.11)	(-2.00)	(-3.53)
Mom	-0.28	0.23	0.31	0.89	0.05
	(-0.52)	(0.66)	(0.41)	(0.95)	(0.05)
AG	-0.41***	-0.23**	0.23	-0.44	0.23
	(-2.61)	(-2.34)	(0.63)	(-1.24)	(0.42)
GP	0.01	0.02	0.01	0.04***	0.02
	(0.72)	(1.10)	(0.75)	(2.91)	(0.66)
Turnover	-0.06**	-0.05	-0.06*	-0.07	-0.19*
	(-2.03)	(0.62)	(-1.84)	(-1.43)	(-1.94)
Ind_mom	1.06**	1.05**	1.10**	1.14**	1.03**
	(2.51)	(2.09)	(2.11)	(2.12)	(2.33)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Obs.	113,851	106,330	74,794	29,275	9,782
R^2	0.12	0.12	0.13	0.19	0.28

Panel B: *Par-Sub*	(1)	(2)	(3)	(4)	(5)
*100	Global	Global ex USA	Asia-Pacific	Europe	North America
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Par_{i,t-1}$	1.72***	1.40***	1.90***	0.80***	2.50***
	(6.48)	(5.69)	(6.17)	(3.56)	(3.72)
Ln(Size)	-0.15***	-0.13***	-0.13***	-0.05	-0.40*
	(-3.56)	(-3.04)	(-3.33)	(-0.82)	(-1.70)
Ln(B/M)	0.24**	0.33***	0.33**	0.27**	0.01

	(2.11)	(2.60)	(2.42)	(2.09)	(0.04)
$RET_{i,t-1}$	-1.51	-0.39	0.26	-4.07**	-7.97***
	(-1.20)	(-0.29)	(0.17)	(-2.25)	(-3.28)
Mom	-0.88	-0.63	-0.78	1.12*	-2.48
	(-1.21)	(-0.95)	(-1.06)	(1.65)	(-1.30)
AG	-0.01	-0.03	-0.35**	0.05	0.26
	(-0.01)	(-0.30)	(-2.37)	(0.18)	(0.49)
GP	-0.03***	-0.03***	-0.02	-0.01	-0.02
	(-3.01)	(-2.80)	(-1.31)	(-0.64)	(-1.60)
Turnover	-0.08	0.09	0.10	0.02	0.61
	(0.73)	(0.79)	(0.97)	(0.21)	(1.56)
Ind_mom	0.80**	0.70	0.46	-0.52	-1.16
	(2.34)	(1.12)	(0.73)	(-0.41)	(-0.59)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Obs.	204,207	191,819	136,216	51,771	16,220
R^2	0.08	0.08	0.09	0.16	0.24

Panel C: *Sub-Par*	(1)	(2)	(3)	(4)	(5)
*100	Global	Global ex USA	Asia-Pacific	Europe	North America
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Sub_{i,t}$	12.75***	8.39***	4.32***	9.23***	9.22***
	(7.50)	(4.94)	(13.66)	(4.78)	(7.32)
$Sub_{i,t-1}$	4.44**	3.77*	1.62***	3.57*	2.99**
	(2.45)	(1.85)	(4.40)	(1.81)	(2.34)
$Sub_{i,t-2}$	2.77	2.34	1.03***	2.24	2.03
	(1.52)	(1.11)	(2.86)	(0.91)	(1.55)
$Sub_{i,t-3}$	1.72	1.28	0.51	1.18	0.85
	(0.79)	(0.56)	(1.28)	(0.56)	(0.89)
$Sub_{i,t-4}$	0.69	0.52	0.35	0.70	0.48
	(0.51)	(0.26)	(1.12)	(0.37)	(0.58)
Controls	Yes	Yes	Yes	Yes	Yes
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Obs.	113,851	106,330	74,794	29,275	9,782
R^2	0.17	0.17	0.18	0.27	0.41

Panel D: *Par-Sub*	(1)	(2)	(3)	(4)	(5)
*100	Global	Global ex USA	Asia-Pacific	Europe	North America
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$

$Sub_{i,t}$	3.25***	2.79***	2.95***	1.24***	5.14***
	(9.77)	(12.97)	(13.00)	(7.03)	(9.22)
$Sub_{i,t-1}$	1.36***	0.98***	1.33***	0.63***	1.81***
	(4.79)	(4.30)	(4.64)	(2.66)	(2.71)
$Sub_{i,t-2}$	0.69***	0.69***	0.84***	0.39*	1.12*
	(2.71)	(2.59)	(2.63)	(1.75)	(1.84)
$Sub_{i,t-3}$	0.43	0.33	0.53	0.22	0.65
	(1.54)	(1.58)	(1.39)	(0.74)	(0.99)
$Sub_{i,t-4}$	0.25	0.16	0.30	0.11	0.34
	(0.68)	(0.65)	(1.20)	(0.41)	(0.50)
Controls	Yes	Yes	Yes	Yes	Yes
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Obs.	204,207	191,819	136,216	51,771	16,220
R^2	0.11	0.11	0.12	0.23	0.35

Panel A of Table 2.3 presents the regression results of the excess returns of the focal firm on $Sub_{i,t-1}$ and a vector of control variables in the global sample and various regional samples. The results demonstrate that the coefficient of $Sub_{i,t-1}$ is statistically significant at the 1% level for the global sample, the Asia-Pacific sample, and the North America sample. The results demonstrate that the coefficient of $Sub_{i,t-1}$ is statistically significant at the 5% level for the Global ex USA sample and the Europe sample. In addition, the predictive power of the lagged subsidiaries' returns is not subsumed by reversal, momentum, and industry momentum of the stock return. The results of Panel A indicate that subsidiaries' returns can predict future returns of focal firms after controlling for firm characteristics.

Panel B of Table 2.3 presents the regression results of excess returns of the focal firm on $Par_{i,t-1}$ and a vector of control variables in the global sample and several regional samples. The results demonstrate that the coefficient of $Par_{i,t-1}$ is statistically significant at the 1% level for the global sample and all regional samples. Additionally, the predictive power of lagged parent firms' returns is not subsumed by reversal, momentum, and industry momentum of the stock return. The results of Panel B indicate that parent firms' returns can predict future returns of focal firms after controlling for firm characteristics.

Panel C of Table 2.3 presents the regression results of excess returns of the focal firm on contemporaneous returns and four months of lagged returns on the subsidiaries' portfolio and a vector of control variables in the global sample and several regional samples. My results show that the coefficients of subsidiaries' returns ($Sub_{i,t-1}$, $Sub_{i,t-2}$, $Sub_{i,t-3}$, and $Sub_{i,t-4}$) are always positive but decrease monotonically from month $t-1$ to month $t-4$. The results demonstrate that the coefficient of $Sub_{i,t-1}$ is statistically significant for all five samples. But the coefficient of $Sub_{i,t-2}$ is only statistically significant for the Asia-Pacific sample. The coefficients of $Sub_{i,t-3}$ and $Sub_{i,t-4}$ are not statistically significant for all five samples. The results of Panel C indicate that subsidiaries' information is gradually transmitted into the focal firm's stock price within one month.

Panel D of Table 2.3 presents the regression results of excess returns of the focal firm on contemporaneous returns and four months of lagged returns on the parent firms' portfolio and a vector of control variables in the global sample and several regional samples. My results show that the coefficients of parent firms' returns ($Par_{i,t-1}$, $Par_{i,t-2}$, $Par_{i,t-3}$, and $Par_{i,t-4}$) are always positive but decrease monotonically from month $t-1$ to month $t-4$. The results demonstrate that the coefficients of $Par_{i,t-1}$ and $Par_{i,t-2}$ are statistically significant for all five samples. But the coefficients of $Sub_{i,t-3}$ and $Sub_{i,t-4}$ are not statistically significant for all five samples. The results of Panel D indicate that parent firms' information is gradually transmitted into the focal firm's stock price within two months.

In summary, the cross-sectional regression results indicate the predictive effect of lagged subsidiaries' returns and the predictive effect of lagged parent firms' returns. The predictive effect cannot be subsumed by several firm characteristics. The predictive pattern is consistent with a gradual diffusion of information along ownership links.

2.3.3 Controlling for Other Inter-firm Links

In addition, I test whether the predictive power of ownership-linked firms cannot be subsumed by other inter-firm momentum. I test a series of inter-firm momentum variables. $Sup\_Ind_{i,t-1}$ and $Cus\_Ind_{i,t-1}$ are the supplier industry return and the customer industry return of focal firm i in the previous month (Menzly and Ozbas, 2010). $Cus_{i,t-1}$ is the customer return of focal firm i in the previous month (Cohen and Frazzini, 2008). $PC_{i,t-1}$ is the pseudo-conglomerate portfolio return of focal firm i in the previous month (Cohen and Lou, 2012). $SA_{i,t-1}$ is the strategic alliance partners' portfolio return of focal firm i in the previous month (Cao et al., 2016). $Tech_{i,t-1}$ is the technological partners' portfolio return of focal firm i in the previous month (Lee et al., 2019). $Geo_{i,t-1}$ is the average return of all other stocks headquartered in the same city of U.S. 20 largest cities in the previous month (Parsons et al., 2019). $CS_{i,t-1}$ is the weighted average return of stocks that are connected through shared analyst coverage in the previous month (Ali and Hirshleifer, 2019). I also add control variables of Table 2.3 in all regressions. For brevity, these control variables are not reported.

Table 2.4: Controlling for Other Inter-firm Links

This table reports the results of cross-sectional Fama and MacBeth (1973) forecasting regressions. This table reports the excess return of focal firm i, $RET_{i,t}$ is regressed on the lagged one-monthly returns of ownership-linked firm peers ($Sub_{i,t-1}$ or $Par_{i,t-1}$), inter-firm momentum ($Sup\_Ind_{i,t-1}$, $Cus\_Ind_{i,t-1}$, $Cus_{i,t-1}$, $PC_{i,t-1}$, $SA_{i,t-1}$, $Tech_{i,t-1}$, $Geo_{i,t-1}$, or $CS_{i,t-1}$), and a vector of control variables, including industry momentum and firm characteristics in Table 2.3. For brevity, coefficients of control variables in regressions are not reported. $Sup\_Ind_{i,t-1}$ and $Cus\_Ind_{i,t-1}$ are the supplier industry return and the customer industry return of focal firm i in the previous month (Menzly and Ozbas, 2010). $Cus_{i,t-1}$ is the customer return of focal firm i in the previous month (Cohen and Frazzini, 2008). $PC_{i,t-1}$ is the pseudo-conglomerate portfolio return of focal firm i in the previous month (Cohen and Lou, 2012). $SA_{i,t-1}$ is the strategic alliance partners' portfolio return of focal firm i in the previous month (Cao et al., 2016). $Tech_{i,t-1}$ is the technological partners' portfolio return of focal firm i in the previous month (Lee et al., 2019). $Geo_{i,t-1}$ is the average return of all other stocks headquartered in the same city of U.S. 20 largest cities in the previous month (Parsons et al., 2019). $CS_{i,t-1}$ is the weighted average return of stocks that are connected through shared analyst coverage in the previous month (Ali and Hirshleifer, 2019). T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries in US market from January 2008 to December 2017.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
*100	US	US	US	US	US	US	US	US	US	US	US
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Sub_{i,t-1}$	5.32***	4.78***	4.84***	4.72***	4.52***	4.27***	4.40***	3.95***	3.57**	3.76**	3.00**
	(3.66)	(3.08)	(3.11)	(3.05)	(2.94)	(2.81)	(2.88)	(2.64)	(2.44)	(2.54)	(2.13)
$Sup\_Ind_{i,t-1}$		0.66		0.42							0.45
		(1.10)		(0.72)							(0.78)
$Cus\_Ind_{i,t-1}$			3.18**	2.19							2.63*
			(2.04)	(1.45)							(1.68)
$Cus_{i,t-1}$					2.82**						1.72
					(2.27)						(1.53)

$PC_{i,t-1}$						2.88**					1.82
						(2.16)					(1.51)
$SA_{i,t-1}$							0.71				0.56
							(1.51)				(1.23)
$Tech_{i,t-1}$								2.11**			1.53
								(2.05)			(1.40)
$Geo_{i,t-1}$									3.10**		1.63
									(2.34)		(1.26)
$CS_{i,t-1}$										3.66**	1.74
										(2.19)	(1.07)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7,521	7,202	7,202	7,202	3,424	4,673	3,955	4,357	7,080	6,498	2,825
R^2	0.21	0.21	0.22	0.22	0.22	0.22	0.21	0.22	0.22	0.22	0.24

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
*100	US	US	US	US	US	US	US	US	US	US	US
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Par_{i,t-1}$	2.81***	2.39***	2.41***	2.36***	2.32***	2.26***	2.29***	2.17**	2.07**	2.12**	1.91**
	(4.32)	(3.14)	(3.21)	(3.02)	(2.89)	(2.64)	(2.76)	(2.32)	(1.99)	(2.13)	(2.37)
$Sup\_Ind_{i,t-1}$		0.36		0.20							0.18
		(1.12)		(0.65)							(0.60)
$Cus\_Ind_{i,t-1}$			1.27*	1.19*							0.82
			(1.93)	(1.76)							(1.47)

$Cus_{i,t-1}$					0.78***						0.45
					(2.78)						(1.60)
$PC_{i,t-1}$						0.40					0.25
						(0.33)					(0.22)
$SA_{i,t-1}$							0.67				0.52
							(1.42)				(1.25)
$Tech_{i,t-1}$								1.75**			1.30*
								(2.44)			(1.82)
$Geo_{i,t-1}$									1.62**		1.27*
									(2.32)		(1.94)
$CS_{i,t-1}$										1.35**	0.67*
										(2.54)	(1.72)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	12,388	11,862	11,862	11,862	5,640	7,697	6,515	7,176	11,662	10,703	4,654
R^2	0.18	0.18	0.18	0.18	0.19	0.19	0.18	0.19	0.19	0.19	0.21

Column 1 of Table 2.4 shows the initial result without inter-firm momentum controls. Columns 2-10 show that the predictor $Sub_{i,t-1}$ or $Par_{i,t-1}$ cannot be subsumed by other inter-firm links, such as supplier industry and customer industry returns, customer returns, 'pseudo-conglomerate' portfolio returns, alliance partners' returns, and technological partners' returns, geographic peers' returns, and shared analyst coverage peers' returns, respectively. In column 11, I find that coefficient for $Sub_{i,t-1}$ or $Par_{i,t-1}$ remains statistically significant at 5% level after adding all these inter-firm variables. The coefficients of most inter-firm momentum variables become economically tiny and statistically insignificant. To sum up, these results indicate that I find two new inter-firm predictors which cannot be explained by industry momentum, a series of firm characteristics, and other known inter-firm predictors.

2.3.4 Performance of Sub-predictors

In this section, I conduct Fama and MacBeth (1973) regressions to compare the predictive power of two sub-predictors after adding control variables. The dependent variable is the excess returns of focal firm ($RET_{i,t}$) and the explanatory variable of interest are lagged returns of the sub-predictors.

$Local\ Sub_{i,t-1}$ are the local subsidiaries' returns of focal firm i in the previous month. $Foreign\ Sub_{i,t-1}$ are the foreign subsidiaries' returns of focal firm i in the previous month. $Same\ Ind\ Sub_{i,t-1}$ are the same industrial subsidiaries' returns of focal firm i in the previous month. $Diff\ Ind\ Sub_{i,t-1}$ are the different industrial subsidiaries' returns of focal firm i in the previous month. $Major\ Sub_{i,t-1}$ are the major (>50% shareholding percentage) ownership subsidiaries' returns of focal firm i in the previous month. $Minor\ Sub_{i,t-1}$ are the minor (<=50% shareholding percentage) ownership subsidiaries' returns of focal firm i in the previous month. $Same\ name\ Sub_{i,t-1}$ are the same name subsidiaries' returns of focal firm i in the previous month. $Diff\ name\ Sub_{i,t-1}$ are the different name subsidiaries' returns of focal firm i in the previous month. $Dir\ Sub_{i,t-1}$ are the directly linked subsidiaries' returns of focal firm i in the previous month. $Indir\ Sub_{i,t-1}$ are the indirectly linked subsidiaries' returns of focal firm i in the previous month.

$Local\ Par_{i,t-1}$ are the local parent firms' returns of focal firm i in the previous month. $Foreign\ Par_{i,t-1}$ are the foreign parent firms' returns of focal firm i in the previous month. $Same\ Ind\ Par_{i,t-1}$ are the same industrial parent firms' returns of focal firm i in the previous month. $Diff\ Ind\ Par_{i,t-1}$ are the different industrial parent firms' returns of focal firm i in the previous month. $Major\ Par_{i,t-1}$ are the major (>50% shareholding percentage) ownership parent firms' returns of focal firm i in the previous month. $Minor\ Par_{i,t-1}$ are the minor (<=50% shareholding percentage) ownership parent firms' returns of focal firm i in the previous month. $Same\ name\ Par_{i,t-1}$ are the same name parent firms' returns of focal firm i in the previous month. $Diff\ name\ Par_{i,t-1}$ are the different name parent firms' returns of focal firm i in the previous month. $Dir\ Par_{i,t-1}$ are the directly linked parent firms' returns of focal firm i in the previous month. $Indir\ Par_{i,t-1}$ are the indirectly linked parent firms' returns of focal firm i in the previous month.

Table 2.5: Performances of sub-predictors

This table compares the performances of sub-predictors by using Fama and MacBeth (1973) regressions. In Panel A, the regressors of interest are local subsidiaries, foreign subsidiaries, same industrial subsidiaries, different industrial subsidiaries, major subsidiaries, minor subsidiaries, same name subsidiaries, different name subsidiaries, directly linked subsidiaries, indirectly linked subsidiaries. In Panel B, the regressors of interest are local parent firms, foreign parent firms, same industrial parent firms, different industrial parent firms, major parent firms, minor parent firms, same name parent firms, different name parent firms, directly linked parent firms, indirectly linked parent firms. Control variables are same as in Table 2.3. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A															
Excess return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
*100	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Local\ Sub_{i,t-1}$	5.24*		3.39												
	(1.82)		(0.95)												
$Foreign\ Sub_{i,t-1}$		10.23***	9.45***												
		(3.56)	(3.28)												
$Same\ Ind\ Sub_{i,t-1}$				4.13*		2.35									
				(1.88)		(1.12)									
$Diff\ Ind\ Sub_{i,t-1}$					7.21***	6.48**									
					(2.63)	(2.32)									
$Major\ Sub_{i,t-1}$							4.83*		2.31						
							(1.75)		(0.98)						
$Minor\ Sub_{i,t-1}$								5.87***	5.22**						
								(2.60)	(2.32)						

$Same\ name\ Sub_{i,t-1}$										3.52**		1.98*			
										(2.20)		(1.73)			
$Diff\ name\ Sub_{i,t-1}$											4.39***	4.19***			
											(2.78)	(2.64)			
$Dir\ Sub_{i,t-1}$													2.82*		1.62
													(1.90)		(1.33)
$Indir\ Sub_{i,t-1}$														4.23***	3.46**
														(2.89)	(2.26)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	15,232	15,232	15,232	17,078	17,078	17,078	19,924	19,924	19,924	18,215	18,215	18,215	15,939	15,939	15,939
R^2	0.10	0.11	0.12	0.10	0.11	0.11	0.10	0.11	0.11	0.10	0.11	0.12	0.10	0.11	0.11

Panel B Excess return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
*100	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Local\ Par_{i,t-1}$	2.02**		1.37*												
	(2.44)		(1.80)												
$Foreign\ Par_{i,t-1}$		4.11***	3.08***												
		(3.21)	(2.95)												
$Same\ Ind\ Par_{i,t-1}$				2.04**		1.29									
				(2.16)		(1.60)									
$Diff\ Ind\ Par_{i,t-1}$					4.29***	3.21**									

					(3.69)	(2.47)									
$Major\ Par_{i,t-1}$							1.89**		1.06						
							(2.05)		(1.45)						
$Minor\ Par_{i,t-1}$								4.31***	3.23***						
								(4.35)	(3.17)						
$Same\ name\ Par_{i,t-1}$										3.06*		2.32			
										(1.93)		(1.59)			
$Diff\ name\ Par_{i,t-1}$											6.32***	4.57***			
											(3.77)	(2.83)			
$Dir\ Par_{i,t-1}$													2.65*		1.32
													(1.88)		(1.33)
$Indir\ Par_{i,t-1}$														4.85***	3.29**
														(3.52)	(2.50)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	24,764	24,764	24,764	30,056	30,056	30,056	35,422	35,422	35,422	32,203	32,203	32,203	27,927	27,927	27,927
R^2	0.08	0.09	0.10	0.08	0.09	0.09	0.08	0.09	0.10	0.08	0.09	0.10	0.08	0.09	0.09

(1) Performance of local firms vs. foreign firms

In columns (1)-(3) of Panel A of Table 2.5, I find that foreign subsidiaries have larger predictive power than local subsidiaries due to larger coefficient and t-statistic value. The predictive information of foreign subsidiaries can absorb the predictive information of local subsidiaries. In columns (1)-(3) of Panel B of Table 2.5, I find that foreign parent firms have larger predictive power than local parent firms due to larger coefficient and t-statistic values. The predictive information of foreign parent firms can absorb the predictive information of local parent firms.

These results are consistent with the findings in Huang (2015). Huang (2015) finds that investors have difficulties to promptly process different language, cultural, and time zone foreign operation information. She finds that the predictive power of foreign operation information can absorb the predictive power of local operation information. My results show that investors are also difficult to promptly process foreign ownership-linked firms' value-relevant information.

(2) Performance of same industrial firms vs. different industrial firms

In columns (4)-(6) of Panel A of Table 2.5, I find that different industrial subsidiaries have larger predictive power than same industrial subsidiaries due to larger coefficient and t-statistic value. The predictive information of different industrial subsidiaries can absorb the predictive information of same industrial subsidiaries. In columns (4)-(6) of Panel B of Table 2.5, I find that different industrial parent firms have larger predictive power than same industrial parent firms due to larger coefficient and t-statistic values. The predictive information of different industrial parent firms can absorb the predictive information of same industrial parent firms.

The explanation is that there are plenty of industry analysts to improve investors prompt reaction to same industrial firms' information, comparing with fewer analyst coverages to multiple industries. These results are consistent with the findings in Ginglinger et al. (2018). Ginglinger et al. (2018) find that when entities are operating in different industries, it may be harder for investors to comprehend these entities and to promptly process the information released by these entities. My results show that investors are difficult to promptly process different industrial ownership-linked firms' value-relevant information.

(3) Performance of major firms vs. minor firms

In columns (7)-(9) of Panel A of Table 2.5, I find that minor subsidiaries have larger predictive power than major subsidiaries due to larger coefficient and t-statistic value. The predictive information of minor subsidiaries can absorb the predictive information of major subsidiaries. In columns (7)-(9) of Panel B of Table 2.5, I find that minor parent firms have larger predictive power than major parent firms due to larger coefficient and t-statistic values. The predictive information of minor parent firms can absorb the predictive information of major parent firms.

There are two explanations. First, investors have larger uncertainty to information and news of minor ownership-linked firms rather than major ownership-linked firms. It delays investors' reaction to information from minor ownership-linked firms. Second, investors believe that minor ownership-linked firms' information or news are not important than that of major ownership-linked firms. Therefore, investors choose to ignore the minor information. These results are consistent with the findings in Ginglinger et al. (2018). Ginglinger et al. (2018) find that when entities are minor or not important in the group, it may be harder for investors to comprehend these entities and to promptly process the information released by these entities. My results show that investors are difficult to promptly process minor ownership-linked firms' value-relevant information.

(4) Performance of same name firms vs. different name firms

In columns (10)-(12) of Panel A of Table 2.5, I find that different name subsidiaries have larger predictive power than same name subsidiaries due to larger coefficient and t-statistic value. The predictive information of different name subsidiaries can absorb the predictive information of same name subsidiaries. In columns (10)-(12) of Panel B of Table 2.5, I find that different name parent firms have larger predictive power than same name parent firms due to larger coefficient and t-statistic values. The predictive information of different name parent firms can absorb the predictive information of same name parent firms.

The economic explanation is that investors may have lower attention to information of different name ownership-linked firms whose names do not reveal any connections. Therefore, Investors' lower attention lead to stronger predictive power of different name ownership-linked firms. These results are consistent with the findings in Ginglinger et al. (2018). Ginglinger et al. (2018) find that when entities whose names do not reveal any connection, it may be harder for investors to comprehend these entities and to promptly process the information released by these entities. My results show that investors are difficult to promptly process different name ownership-linked firms' value-relevant information.

(5) Performance of direct firms vs. indirect firms

In columns (13)-(15) of Panel A of Table 2.5, I find that indirectly linked subsidiaries have larger predictive power than directly linked subsidiaries due to larger coefficient and t-statistic value. The predictive information of indirectly linked subsidiaries can absorb the predictive information of directly linked subsidiaries. In columns (13)-(15) of Panel B of Table 2.5, I find that indirectly linked parent firms have larger predictive power than directly linked parent firms due to larger coefficient and t-statistic values. The predictive information of indirectly linked parent firms can absorb the predictive information of directly linked parent firms.

The economic intuition is that investors' myopia effect delays investors' reaction to farther information from indirectly ownership-linked firms. These results are consistent with the findings in Ginglinger et al. (2018). Ginglinger et al. (2018) find that when entities are far away from the focal firm investors, it may be harder for investors to notice these entities and to promptly process the information released by these entities. My results show that investors are difficult to promptly process indirectly linked ownership-linked firms' value-relevant information.

2.3.5 Robustness

This section supplies information about the additional analyses and stability checks conducted to guarantee the robustness of the main empirical results. I perform univariate portfolio sorts in the global samples to reveal the results of different stability and robustness checks. Table 2.6 reports the results of diverse robustness checks. All abnormal returns are adjusted using the Fama and French (2018) six-factor model.

First, I conduct univariate portfolio sorts in two sub-period samples. Second, I conduct univariate portfolio sorts of only using local ownership-linked firms and only using foreign ownership-linked firms. In addition, I conduct univariate portfolio sorts of only using same industrial ownership-linked firms and only using different industrial ownership-linked firms. Finally, I conduct univariate portfolio sorts of only using major (>50% shareholding percentage) ownership-linked firms and only using minor (<=50% shareholding percentage) ownership-linked firms.

Table 2.6: Robustness

This table presents robustness checks. I perform univariate portfolio sorts on the global sample and value-weighted returns for five quintile portfolios, and the 5-1 difference portfolio using a global version of the Fama and French (2018) six-factor model. The six risk factors are obtained from the homepage of Kenneth French. Panel A reports results of subsidiary-parent return predictability. Panel B reports results of parent-subsidiary return predictability. Column (1) and (2) report two subperiods' results of univariate portfolio sorts. Column (3) reports the results of univariate portfolio sorts of only using local ownership-linked firms. Column (4) reports the results of univariate portfolio sorts of only using foreign ownership-linked firms. Column (5) reports the results of univariate portfolio sorts of only using same industrial ownership-linked firms. Column (6) reports the results of univariate portfolio sorts of only using different industrial ownership-linked firms. Column (7) reports the results of univariate portfolio sorts of only using major (>50% shareholding percentage) ownership-linked firms. Column (8) reports the results of univariate portfolio sorts of only using minor (<=50% shareholding percentage) ownership-linked firms. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms from twenty-three developed markets from January 2008 to December 2017.

Panel A: *Sub – Par*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Value Weights	1st period	2nd period	Local	Foreign	Same	Different	Major	Minor
1 (Low)	-1.00***	-0.87***	-0.46***	-0.78***	-0.38**	-0.82***	-0.63***	-0.80***
2	-0.37*	-0.51*	-0.24	-0.35*	-0.35**	-0.37*	-0.27*	-0.27
3	0.02	-0.37	-0.16	-0.29	-0.15	-0.38*	-0.12	-0.31
4	-0.11	-0.10	-0.12	-0.31*	-0.13	-0.26	-0.11	-0.38*
5 (High)	0.25	0.10	0.22	0.23	0.11	0.19	0.12	0.14
5-1	1.25***	0.97***	0.68***	1.01***	0.49***	1.01***	0.75***	0.95***
	(6.29)	(3.71)	(4.35)	(5.36)	(2.91)	(4.88)	(4.73)	(4.90)

Panel B: *Par – Sub*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Value Weights	1st period	2nd period	Local	Foreign	Same	Different	Major	Minor

1 (Low)	-0.53	-0.53*	-0.50*	-0.90**	-0.49*	-1.23***	-0.58**	-0.64**
2	-0.40	-0.22	-0.06	-0.48*	-0.26	-0.47*	-0.10	-0.44*
3	-0.72*	-0.15	-0.15	-0.31	-0.09	-0.19	-0.14	-0.14
4	-0.42	0.12	0.02	-0.37	0.05	-0.07	-0.05	-0.25
5 (High)	0.62*	0.23	0.06	0.02	0.24	0.01	0.09	0.16
5-1	1.15***	0.76**	0.56*	0.92***	0.73**	1.24***	0.67**	0.80***
	(3.20)	(2.19)	(1.75)	(2.86)	(2.36)	(4.00)	(2.43)	(3.36)

In Panel A, I test the robustness of subsidiary-parent return predictability. Firstly, I examine the samples of portfolio abnormal returns for the subperiods. In the period between January 2008 and December 2012, I find that the value-weighted parent firms' portfolio alpha is 1.25 (t-statistic = 6.29). In the period between January 2013 and December 2017, I find that the value-weighted parent firms' portfolio alpha is 0.97 (t-statistic = 3.71). I also examine the subsamples of predictors based on different classifications. Both local and foreign subsidiaries can predict future returns of the parent firm. The value-weighted portfolio abnormal returns of using local subsidiaries and using foreign subsidiaries are 0.68% (t-statistic = 4.35) and 1.01% (t-statistic = 5.36) respectively. Both same industrial subsidiaries and different industrial subsidiaries can predict future returns of the parent firm. The value-weighted portfolio abnormal returns of using same industrial subsidiaries and using different industrial subsidiaries are 0.49% (t-statistic = 2.91) and 1.01% (t-statistic = 4.88) respectively. Both major ownership subsidiaries and minor ownership subsidiaries can predict future returns of the parent firm. The value-weighted portfolio abnormal returns of using major ownership subsidiaries and using minor ownership subsidiaries are 0.75% (t-statistic = 4.73) and 0.95% (t-statistic = 4.90) respectively. The results of Panel A indicate that subsidiary-parent return predictability is robust in different sub-samples.

In Panel B, I test the robustness of parent-subsidiary return predictability. In the period between January 2008 and December 2012, I find that the value-weighted subsidiaries' portfolio alpha is 1.15 (t-statistic = 3.20). In the period between January 2013 and December 2017, I find that the value-weighted subsidiaries' portfolio alpha is 0.76 (t-statistic = 2.19). Both local parent firms and foreign parent firms can predict future subsidiary returns. The value-weighted portfolio abnormal returns of using local parent firms and using foreign parent firms are 0.56% (t-statistic = 1.75) and 0.92% (t-statistic = 2.86) respectively. Both same industrial parent firms and different industrial parent firms can predict future subsidiary returns. The value-weighted portfolio abnormal returns of using same industrial parent firms and using different industrial parent firms are 0.73% (t-statistic = 2.36) and 1.24% (t-statistic = 4.00) respectively. Both major parent firms and minor parent firms can predict future subsidiary returns. The value-weighted portfolio abnormal returns of using major parent firms and using minor parent firms are 0.67% (t-statistic 2.43) and 0.80% (t-statistic = 3.36) respectively. The results of Panel B indicate that parent-subsidiary return predictability is robust in different sub-samples.

2.4 Market-wide Sentiment and Attention

Anomalies can be driven by two common behavioral forces, namely 'subjective' sentiment, which represents investors' subjective biased beliefs, and 'objective' limited attention, which represents investors' objective cognitive constraints. I use the market-wide sentiment of Baker and Wurgler (2006) and the market-wide attention indices of Duan et al. (2018) to examine whether the abnormal returns discovered based on the subsidiary momentum and parent momentum can be explained by market-wide sentiment and market-wide attention. I expect that abnormal returns will be higher during high investor sentiment periods due to the binding of short-selling constraints and optimistic investors' biases (Stambaugh et al., 2012). It is expected that abnormal returns will be higher during low investor attention periods due to investors' limited reaction across ownership links (Duan et al., 2018).

Table 2.7: Market-wide Sentiment and Attention

This table reports Fama and French (2018) six-factor alphas in different sentiment and attention periods. In this table, I report focal firms' six-factor alphas. I equally divide whole period into two sentiment subperiods, high sentiment period and low sentiment period, based on the market sentiment indices. I equally divide whole period into two attention subperiods, high attention period and low attention period, based on market attention indices. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A	(1)	(2)	(3)	(4)	(5)
Sub – Par	Global	Global ex USA	Asia-Pacific	Europe	North America
High Sentiment	1.23***	1.27***	1.18***	1.69***	1.71***
Low Sentiment	0.91**	0.94*	0.88*	1.25**	1.27*
High Attention	0.80**	0.83*	0.77*	1.10**	1.12*

Low Attention	1.34***	1.38***	1.29***	1.84***	1.86***

Panel B	(1)	(2)	(3)	(4)	(5)
Par – Sub	Global	Global ex USA	Asia-Pacific	Europe	North America
High Sentiment	1.08***	1.15***	2.09***	1.69***	1.08***
Low Sentiment	0.80*	0.85*	1.55**	1.25*	0.63
High Attention	0.71*	0.75*	1.37**	1.10*	0.57
Low Attention	1.18***	1.25***	2.28***	1.84***	1.18***

Panel A of Table 2.7 shows that parent firms' abnormal returns are higher in a high sentiment period and lower in a low sentiment period. In a high sentiment period, abnormal returns in all five regional markets are strongly significant at the 1% level and large in magnitude from 118 basis points to 171 basis points. However, in a low sentiment period, abnormal returns in three regional markets are only weakly significant at the 10% level and small in magnitude from 88 basis points to 127 basis points. Panel A of Table 2.7 shows that parent firms' abnormal returns are higher in a low attention period and lower in a high attention period. In a low attention period, abnormal returns in all five regional markets are strongly significant at the 1% level and large in magnitude from 129 basis points to 186 basis points. However, in a high attention period, abnormal returns in three regional markets are only weakly significant at the 10% level and small in magnitude from 77 basis points to 112 basis points. These results are consistent with Stambaugh et al. (2012) and Duan et al. (2018). Abnormal returns are higher during high investor sentiment periods and low investor attention periods.

Panel B of Table 2.7 shows that subsidiaries' abnormal returns are higher in a high sentiment period and lower in a low sentiment period. In a high sentiment period, abnormal returns in four regional markets are strongly significant at the 1% level and large in magnitude from 108 basis points to 209 basis points. However, in a low sentiment period, abnormal returns in three regional markets are only weakly significant at the 10% level and small in magnitude from 80 basis points to 125 basis points. Panel B of Table 2.7 shows that subsidiaries' abnormal returns are higher in a low attention period and lower in a high attention period. In a low attention period, abnormal returns in four regional markets are strongly significant at the 1% level and large in magnitude from 118 basis points to 228 basis points. However, in a high attention period, abnormal returns in three regional markets are only weakly significant at the 10% level and small in magnitude from 71 basis points to 110 basis points. These results are consistent with Stambaugh et al. (2012) and Duan et al. (2018). Abnormal returns are higher during high investor sentiment periods and low investor attention periods.

2.5 Change status of ownership links

In this section, I conduct a test of ownership-linked firms' returns forecasting future returns of focal firm, by examining a particular setting where I can follow the same firm without ownership links and with ownership links. I restrict the analysis to solely those firms without ownership links that transition to with ownership links, through mergers and acquisitions, and initial public offerings of firms. The advantage of this test is that I can now examine the time lags in information updating of the exact same firms when them without ownership links that transition to them with ownership links.

The sanity is that, when the same firm has not ownership linked firms, its ownership-linked firms should have relatively weaker or insignificant predictability over its future returns. However, when the same firm has ownership linked firms, its ownership-linked firms should be a significant and positive predictor of its future return.

Table 2.8 Change Status of Ownership Links

This table reports Fama-MacBeth forecasting regressions of stock returns in two subsamples. I identify all cases in which a firm without ownership link transitions into the firm with ownership link. I then include observations within two years prior to the status change in the firm without the ownership link, and those within two years subsequent to the status change in the firm with the ownership link. In columns (1) and (3), the dependent variable is the monthly return of the parent firm, the independent variable is the monthly return of the subsidiary; In columns (2) and (4), the dependent variable is the excess return of the subsidiary, the independent variable is the monthly return of the parent firm. Control variables are same as in Table 2.3 and are unreported for brevity. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the

10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

	Before ownership link		After ownership link	
	(1)	(2)	(3)	(4)
*100	Global	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Sub_{i,t-1}$	2.02			
	(1.23)			
$Par_{i,t-1}$		0.48*		
		(1.81)		
$Sub_{i,t-1}$			4.52***	
			(2.67)	
$Par_{i,t-1}$				1.55***
				(4.06)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	4,554	8,168	4,554	8,168
R^2	0.07	0.03	0.11	0.07

I implement this test by identifying all cases in which a firm without the ownership link transitions into a firm with the ownership link. I then include observations within two years prior to the link change, and those within two years subsequent to the link change. I conduct Fama-MacBeth return predictive regressions and the results are reported in Table 2.8. When a firm has not ownership links, its predictor is insignificant or weakly significant. However, when that firm has ownership links, its predictor becomes statistically significant at 1% level. This suggests that linked firms have predictive power after firms are ownership connected.

2.6 Transaction Costs

In this section, I test the impact of trading costs on trading strategy. Following Cao et al. (2016), I calculate trading costs. I obtain the closing bid and ask prices for 23 developed markets' stocks. $cost_i$ is half the bid–ask spread divided by the stock price for stock i. The number of stocks that enter the long portfolio is denoted as $L1$; the number of stocks that exit the long portfolio is denoted as $L3$; and the number of stocks that remain in the portfolio is denoted as $L2$. The trading costs for the long side in month t are:

$$Cost_{long,t} = \frac{\sum_{L1} cost_i + \sum_{L2} cost_i}{\frac{(L1+L2)+(L3+L2)}{2}}$$

The denominator denotes the average number of stocks in the long portfolio in month t. I can also obtain the trading costs for the short side by using the same analysis.

The monthly trading costs are averaged over time. This reduces subsidiary momentum trading strategy profits by 22 basis points from 107 basis points (Fama and French (2018) six-factor alpha) per month to 85 basis points per month (t-statistic = 4.86), and reduces parent firm momentum trading strategy profits by 36 basis points from 94 basis points (Fama and French (2018) six-factor alpha) per month to 58 basis points per month (t-statistic = 1.87). It indicates that my trading strategy is still profitable after considering trading costs.

2.7 Conclusion

This chapter analyzes subsidiary-parent return predictability and parent-subsidiary return predictability by using a sample of firms from twenty-three developed countries worldwide. Lagged one-monthly returns of subsidiaries can predict the following monthly returns of parent firms. Lagged one-monthly returns of parents can predict the following monthly returns of subsidiaries. Two trading strategies can generate abnormal returns, which cannot be explained felicitously by risk factors and firm characteristics.

In addition, I compare the performance of sub-predictors. I find that ownership-linked firms consisting of foreign firms, different industrial firms, minor firms, different name firms, or indirect firms have a larger predictive power over the future monthly returns of focal firms.

The contribution of this chapter is the new evidence of inter-firm return predictability in the ownership networks. These new inter-firm return predictabilities are not only an interesting practical fact with implications for investing and hedging, but also have essential implications for new asset pricing factors.

CHAPTER 3 — Mechanisms of The Return Predictability along Ownership Links

3.1 Introduction

In the last chapter, I studied inter-firm return predictabilities along ownership links. I found subsidiary-parent return predictability and parent-subsidiary return predictability on a global scale and in various regional samples. The returns from these strategies cannot be explained by risk factors, and firm characteristics. In this chapter, I test which mechanisms can drive inter-firm return predictabilities along ownership links. I propose four underlying mechanisms to explain the return predictability in complex ownership network. First, the investors' limited attention to focal firms, ownership links, or ownership-linked firms may lead to the return predictability. Second, the limits to arbitrage, including high costs of arbitrage and difficult to leverage with borrowing capital, may explain the return predictability. Third, the opaque internal information of the conglomerate, such as active internal capital market and tunneling effect, could generate the return predictability. Finally, the information complexity of focal firms or ownership-linked firms may delay investors' prompt response to update price and lead to the return predictability.

The main contribution of this chapter is the mechanisms it finds to explain the return predictability along ownership links. I find that not only traditional mechanisms, including investors' limited attention and limits to arbitrage, can explain the inter-firm return predictability, but also the new mechanisms, including the opaque internal information and information complexity, can also explain the inter-firm return predictability. The two new mechanisms provide new perspectives to advance the understanding of the return predictability among the inter-firm networks. The two new mechanisms also have essential implications for behavioral finance models and theories.

3.1.1 The Investors' Limited Attention

The investors' limited attention to focal firms may explain inter-firm return predictability. For example, Cohen and Frazzini (2008) find that investors' limited attention to suppliers leads to the return predictability from customers to suppliers. Cao et al. (2016) find that lagged stock returns of strategic alliance partners can forecast stock returns of focal firms, since investors have lower attention to these focal firms. Therefore, I propose that investors' limited attention to focal firms can explain the return predictability along ownership links. I use three common variables which have been widely used by previous studies (Cohen and Frazzini, 2008; Cohen and Lou, 2012; Huang, 2015), such as turnover, analyst coverage, and institutional investor holdings, to measure investors' limited attention to focal firms.

Investors may have lower attention to new ownership links. For example, when the parent firm has just acquired the equity of the other firm, investors may have lower attention to this new ownership link. However, investors may have higher attention to other old ownership links. Therefore, I propose that investors' lower attention to new ownership links could lead to the return predictability. I use firms' merger and acquisition data to identify new ownership links and old ownership links.

In Chapter 2, I find that investors have lower attention to foreign firms, different industrial firms, minor firms, different name firms, and indirect firms. Therefore, I propose that when the ownership-linked firms are consisted of these firms to forecast stock returns of focal firms, the return predictability is more pronounced.

3.1.2 The Limits to Arbitrage

The high costs of arbitrage may explain inter-firm return predictabilities along ownership links. For instance, Cao et al. (2016) find that high costs of arbitrage lead to return predictability between strategic alliance partners. More recently, Lee et al. (2019) find that return predictability between technological partners can be explained by the high costs of arbitrage. Shedding lights on these empirical studies which find that high costs of arbitrage can explain return predictability, I want to show that the return predictability along ownership links can be explained by the high costs of arbitrage and that these forecasting patterns are more pronounced among focal firm stocks with less market capitalization, and higher idiosyncratic volatility.

The difficult to leverage with borrowing capital may explain return predictability. Akbas et al. (2015, 2016) find that when there are high capital inflows to hedge funds, hedge funds can better correct stock mispricing. I use broker-dealer capacity to proxy for the level of arbitrage capital and split the sample period into high and low funding liquidity periods. I find that abnormal returns produced from the strategies are higher in low funding liquidity period and lower in high funding liquidity period.

3.1.3 The Opaque Internal Information of The Conglomerate

The opacity of cash flow transfers between subsidiaries in the internal capital market may reduce information processing efficiency. Berger and Ofek (1995) find that internal capital market activities, such as overinvestment and cross-subsidization, in a group decrease information processing efficiency and bring about value discounts. Lamont (1997) finds that investment in nonoil segments of petroleum companies decreases when cash flow in oil segments falls dramatically due to the large plunge of oil prices in 1985. This finding indicates that investment of one subsidiary in a parent firm may depend on the cash flows of other subsidiaries in a parent firm through internal capital markets. I find that the more active internal capital market of the focal firm is, the stronger return predictability is.

Investors may be worried about a potential tunneling effect. Focal firm's investors fear rent extraction from that focal firm by other firms in a group (e.g., Johnson et al., 2000; Dyck and Zingales, 2004; Atanasov et al., 2010). When the ownership-linked firm announces a positive information, but even if the focal firm's investors are aware of the ownership links and expect that the positive information at the level of the ownership-linked firm result from the focal firm, they could be still suspicious about whether this information is positive for the focal firm. Inter-firm tunneling may influence the return predictability along ownership links. I use countries' anti-self-dealing index and public enforcement index to proxy for the possibility of tunneling and split the all countries into high, medium, and low tunneling possibility countries. The abnormal returns are highest in high tunneling possibility countries.

3.1.4 Information Complexity

Investors may have limited capacities to respond promptly to complex information of ownership-linked firms. The more complex the information of ownership-linked firms is, the more stronger return predictability is. For example, Cohen and Lou (2012) find that the complexity of sales information drives the return predictability from standalones to conglomerates. Therefore, I propose that subsidiaries' information complexity and parents' information complexity can drive the return predictability. Investors are difficult to respond promptly to complex subsidiaries' or parent firms' information and their corresponding portfolio returns.

Higher analysts' forecast dispersion may lead to slower information responses and thus analysts' complexity may explain return predictability along ownership links. Chan et al. (1996) find that price continuation comes from a gradual response to information. Hirshleifer (2001) and Daniel et al. (1998, 2001) find that behavioral biases are increased when there is more complex information. Zhang (2006) proposes that behavioral biases are larger and price response is slower when there is larger analysts' forecast dispersion for the firm's value. Therefore, investors are difficult to respond promptly, when there is larger analysts' forecast dispersion.

Investors have limited capacities to analyze information of complex intangibles. Intangibles' complexity could lead to return predictability. Morck and Yeung (1991) find evidence that the value discounts of the firm increase with growth of R&D and advertising expenses. Multinational companies have a higher proportion of intangible assets than domestic companies (Morck and Yeung (1992)), which are associated with higher returns. Hirshleifer et al. (2013) find that more technology-intensive firms are likely to be difficult to value, leading to a slower and potentially stronger information diffusion effect. Therefore, I propose that parent firms and subsidiaries which have more complex intangibles (e.g., larger advertising expenses/market capitalization, or larger the number of employees/market capitalization) are more likely to be mispriced by investors.

The remainder of the chapter is organized as follows. Section 3.2 shows data and methodology of testing mechanisms. Section 3.3 explores investors' limited attention. Section 3.4 tests the limits to arbitrage. Section 3.5 tests the opaque internal information of the conglomerate. In section 3.6, I examine the information complexity. Section 3.7 compares these competing mechanisms. Section 3.8 concludes.

3.2 Data and Methodology

3.2.1 Data

The sample covers parent firms and subsidiaries from twenty-three developed markets. The twenty-three developed markets are based on the MSCI world developed market index as of December 2017. The 23 developed markets include two North American markets (Canada and United States), sixteen European markets (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and United Kingdom), and five Asia-Pacific markets (Australia, Hong Kong, Japan, New Zealand, and Singapore). I collect price, return, and volume data for US firms from the Center for Research in Security Prices (CRSP) and the same data for non-US firms from Thomson Reuter's Eikon. I further collect accounting data for US firms from Compustat and accounting data for non-US firms from Worldscope. Institutional ownership data and analyst data for all firms in the sample are obtained from Thomson Reuters Institutional Holdings (13F) and Thomson Reuters I/B/E/S, respectively. I collect time-varying ownership links and shareholdings data from the FactSet database. I exclude stocks with prices below $5 to avoid market microstructure problems. I cover all industrial firms except firms in the financial sector[22] (with two-digit NAICS code = 52). The sample period is from January 2008 to December 2017 with a total of 120 months.[23] Like other international asset pricing literature, all stocks returns are denominated in USD.[24] Following Fama and French (2012), we use the one-month US T-bill rate for the USA and the remaining countries to calculate monthly excess returns.[25]

3.2.2 Methodology

As for testing mechanisms to subsidiaries-parent return predictability, I construct a dummy variable, $D_{i,t-1}$, which is equal to one if the corresponding mechanism (e.g., investor attention) proxy of firm i in the previous month is above the cross-sectional median of all firms. Then I run Fama-MacBeth

[22] Financial firms are often excluded in empirical asset pricing literature (e.g., Finke and Weigert, 2017, Lee et al., 2019) since the characteristics of accounting variables of financial firms are very different from firms operating in the real economy.
[23] I have only 10 years' historical ownership data due to the data availability.
[24] For example, Griffin (2002) and Fama and French (2012).
[25] My results are stable if we use local currency returns and work with raw returns rather than excess returns.

regressions by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged subsidiaries' returns ($Sub_{i,t-1}$) and the dummy variable ($D_{i,t-1}$).

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,c,t} + \lambda_{2,d,t} + \lambda_{3,t}\, Sub_{i,t-1} + \lambda_{4,t} D_{i,t-1} + \lambda_{5,t} Sub_{i,t-1} \times D_{i,t-1} + \lambda_{6,t}{}'\, X_{i,t-1} + \varepsilon_{i,t},$$

where $RET_{i,t} - R_{f,t}$ is the excess return on the focal firm's stock i in month t; $\lambda_{0,t}$ denotes the intercept; $\lambda_{1,c,t}$ is a country-specific dummy variable which is equal to one if firm i is from country c and zero otherwise; $\lambda_{2,d,t}$ is a industry-specific dummy variable which is equal to one if firm i is from industry d and zero otherwise; $Sub_{i,t-1}$ is the lagged subsidiary stock return in month $t-1$; $X_{i,t-1}$ represents a vector of controls, including $Ln(Size)$ the natural logarithm of the market capitalization (Banz, 1981), $Ln(B/M)$ the natural logarithm of book-to-market equity ratio (Basu, 1983), Mom the cumulative return of stock i from month $t-12$ to $t-2$ (Jegadeesh and Titman, 1993), $RET_{i,t-1}$ the stock return of focal firm i in month $t-1$ (Jegadeesh, 1990; Lo and MacKinlay, 1990), *Turnover* the number of shares traded divided by the number of shares outstanding during a day, averaged over the past twelve months (Rouwenhorst, 1999; Ibbotson et al., 2013), Ind_mom the value-weighted two-digit SIC industry return of the focal firm in month $t-1$

(Grinblatt and Moskowitz, 1999; Nijman et al., 2004), asset growth (AG) the year-over-year growth rate of total assets (Cooper et al., 2008), and gross profitability (GP) the revenue minus cost of goods sold scaled by assets (Novy-Marx, 2013).

If the dummy variable ($D_{i,t-1}$) is one investor attention measure (e.g., institutional ownership, turnover, or analyst coverage), a significantly negative coefficient estimate for $\lambda_{5,t}$ implies that the predictability effect of subsidiaries' returns ($Sub_{i,t-1}$) is lower for firms with high investor attention and vice versa. In other words, investors' limited attention can explain the return predictability.

As for testing mechanisms to parents-subsidiary return predictability, I construct a dummy variable, $D_{i,t-1}$, which is equal to one if the corresponding mechanism (e.g., investor attention) proxy of firm i in the previous month is above the cross-sectional median of all firms. Then I run Fama-MacBeth regressions by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged parent firms' returns ($Par_{i,t-1}$) and the dummy variable ($D_{i,t-1}$).

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,c,t} + \lambda_{2,d,t} + \lambda_{3,t} Par_{i,t-1} + \lambda_{4,t} D_{i,t-1} + \lambda_{5,t} Par_{i,t-1} \times D_{i,t-1} + \lambda_{6,t}{}' X_{i,t-1} + \varepsilon_{i,t},$$

where $RET_{i,t} - R_{f,t}$ is the excess return on the focal firm's stock i in month t; $\lambda_{0,t}$ denotes the intercept; $\lambda_{1,c,t}$ is a country-specific dummy variable which is equal to one if firm i is from country c and zero otherwise; $\lambda_{2,d,t}$ is a industry-specific dummy variable which is equal to one if firm i is from industry d and zero otherwise; $Par_{i,t-1}$ is the lagged parent firm stock return in month $t-1$; $X_{i,t-1}$ represents a vector of controls, including $Ln(Size)$ the natural logarithm of the market capitalization (Banz, 1981), $Ln(B/M)$ the natural logarithm of book-to-market equity ratio (Basu, 1983), Mom the cumulative return of stock i from month $t-12$ to $t-2$ (Jegadeesh and Titman, 1993), $RET_{i,t-1}$ the stock return of focal firm i in month $t-1$ (Jegadeesh, 1990; Lo and MacKinlay, 1990), *Turnover* the number of shares traded divided by the number of shares outstanding during a day, averaged over the past twelve months (Rouwenhorst, 1999; Ibbotson et al., 2013), Ind_mom the value-weighted two-digit SIC industry return of the focal firm in month $t-1$ (Grinblatt and Moskowitz, 1999; Nijman et al., 2004), asset growth (AG) the year-over-year growth rate of total assets (Cooper et al., 2008), and gross profitability (GP) the revenue minus cost of goods sold scaled by assets (Novy-Marx, 2013).

If the dummy variable ($D_{i,t-1}$) is one investor attention measure (e.g., institutional ownership, turnover, or analyst coverage), a significantly negative coefficient estimate for $\lambda_{5,t}$ implies that the predictability effect of parent firms' returns ($Par_{i,t-1}$) is lower for firms with high investor attention and vice versa. In other words, investors' limited attention can explain the return predictability.

Compared with other approaches (e.g., pooled OLS regressions) to deal with panel data, the Fama-MacBeth regressions take into account the cross-correlations and the serial correlation in the error term, so that the t-statistics are much more conservative (Choe et al., 2005). In addition, the Fama-MacBeth regressions are computationally simple to implement and are widely used in the literature of return predictability (Cochrane, 2005; Hou et al., 2018).

3.3 The Investors' Limited Attention

I test whether the results are driven by investors' limited attention to focal firms, ownership links, or ownership-linked firms. I use some proxies for inattention to test this mechanism. Specifically, if investors' limited attention plays an important role, I would expect stronger return predictability when investors have lower attention. I use three common variables to capture investors' inattention to focal firms in the literature (Cohen and Frazzini, 2008; Cohen and Lou, 2012; Huang, 2015; Lee et al., 2019): lower residual institutional ownership, [26] lower turnover, and lower analyst coverage. Residual institutional ownership (Res Inst Own) is institutional ownership of the focal firm orthogonalized with regard to firm size at the end of December in the previous calendar year. Turnover is the focal firm's turnover measured as the average daily turnover in the previous calendar year, and No. Analysts is the number of analysts that cover the focal firm at the end of December in the previous calendar year. A dummy variable, $D_{i,t-1}$, is equal to one if the corresponding investor attention proxy (i.e., Res Inst Own, turnover, or No. Analysts) of focal firm i in the previous month is above the cross-sectional median of all firms. Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged subsidiaries' returns (or the lagged parent firms' returns) and the dummy variable ($D_{i,t-1}$).

Also, I use firms' merger and acquisition data to identify new ownership links and old ownership links. For example, when the parent firm has just acquired the equity of the other firm, investors may have lower attention to this new ownership link. However, investors have higher attention to old ownership links. A dummy variable, $D_{i,t-1}$, is equal to one if the parent firm has just acquired

[26] Note that residual institutional ownership here is the institutional ownership after being orthogonalized with respect to focal firm market capitalization.

the equity of the other firm in the last two years.[27] Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged subsidiaries' returns (or the lagged parent firms' returns) and the dummy variable ($D_{i,t-1}$).

Finally, investors have lower attention to foreign firms, different industrial firms, minor firms, different name firms, and indirect firms. Therefore, I expect that when the ownership-linked firms are consisted of these firms, the return predictability is more pronounced. A dummy variable, $D_{i,t-1}$, is equal to one if the ownership-linked firms are consisted of these firms (i.e., foreign firms, different industrial firms, minor firms, different name firms, or indirect firms). Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged subsidiaries' returns (or the lagged parent firms' returns) and the dummy variable ($D_{i,t-1}$).

Table 3.1: Investors' Limited Attention

This table reports that investors' limited attention mechanisms. In Panel A and B, the dependent variable is the monthly excess return of the parent firm and explanatory variables include the lagged subsidiaries' return ($Sub_{i,t-1}$) and the interaction term between the lagged subsidiaries' return ($Sub_{i,t-1}$) and the dummy variable. In Panel C and D, the dependent variable is the monthly excess return of the subsidiary and explanatory variables include the lagged parent firms' return ($Par_{i,t-1}$) and the interaction term between the lagged parent firms' return ($Par_{i,t-1}$) and the dummy variable. I use different proxy variables to explain the mechanism of investors' limited attention to focal firms, inter-firm linkages, or partial predictor information. Res Inst Own is institutional ownership of the focal firm orthogonalized with regard to firm size at the end of December in previous calendar year. Turnover is the focal firm's

[27] I test new ownership links from one to five years. My results are not influenced.

turnover measured as the average daily turnover in previous calendar year, and No. Analysts is the number of analysts covering the focal firm at the end of December in previous calendar year. The dummy variable that takes the value of one if the proxy variable is above the sample median in the previous month and zero otherwise. New ownership links are dummy variables that take the value of one if the parent firm has just acquired the equity of the other firm in the last two years and zero otherwise. Foreign, Different Industry, Minor, different name, and Indirectly linked are dummy variables that take the value of one if the predictor has corresponding proxy variable information and zero otherwise. All regressions also include the dummy variable itself and lagged control variables. Control variables are same as in Table 2.3 and are unreported for brevity. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A: *Sub – Par*	(1)	(2)	(3)	(4)
*100	Global	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Sub_{i,t-1}$	8.86***	7.77***	8.26***	4.21***
	(2.98)	(2.76)	(2.69)	(3.25)
$Sub_{i,t-1}$ * (Res Inst Own > Median)	-4.23*			
	(-1.87)			
$Sub_{i,t-1}$ * (Turnover > Median)		-3.28*		
		(-1.76)		
$Sub_{i,t-1}$ * (No. Analyst > Median)			-4.44*	
			(-1.89)	
$Sub_{i,t-1}$ * (New Ownership links)				3.78***
				(2.60)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	113,851	113,851	113,851	113,851
R^2	0.12	0.12	0.12	0.12

Panel B: *Sub – Par*	(1)	(2)	(3)	(4)	(5)
*100	Global	Global	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Sub_{i,t-1}$	7.22***	6.12***	5.29***	4.76***	4.39***
	(3.68)	(3.18)	(2.84)	(2.77)	(2.70)
$Sub_{i,t-1}$ * (Foreign)	5.34***				
	(3.12)				
$Sub_{i,t-1}$ * (Different industry)		3.52**			
		(2.16)			
$Sub_{i,t-1}$ * (Minor)			3.29**		

			(2.09)		
$Sub_{i,t-1}$ * (Different name)				2.70**	
				(2.35)	
$Sub_{i,t-1}$ * (Indirectly linked)					2.59**
					(2.03)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	113,851	113,851	113,851	113,851	113,851
R^2	0.14	0.14	0.14	0.13	0.13

Panel C: *Par – Sub*	(1)	(2)	(3)	(4)
*100	Global	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Par_{i,t-1}$	2.21***	2.31***	2.22***	1.01***
	(4.08)	(4.54)	(4.27)	(4.05)
$Par_{i,t-1}$ * (Res Inst Own > Median)	-0.89***			
	(-2.76)			
$Par_{i,t-1}$ * (Turnover > Median)		-0.94***		
		(-2.98)		
$Par_{i,t-1}$ * (No. Analyst > Median)			-0.84**	
			(-2.31)	
$Par_{i,t-1}$ * (New Ownership links)				1.74***
				(2.89)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	204,207	204,207	204,207	204,207
R^2	0.08	0.08	0.08	0.08

Panel D: *Par – Sub*	(1)	(2)	(3)	(4)	(5)
*100	Global	Global	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Par_{i,t-1}$	1.92***	1.65***	1.52***	1.70***	1.49***
	(6.82)	(6.14)	(5.60)	(6.35)	(5.28)
$Par_{i,t-1}$ * (Foreign)	1.10***				
	(3.17)				
$Par_{i,t-1}$ * (Different industry)		0.83**			
		(2.34)			
$Par_{i,t-1}$ * (Minor)			0.94***		
			(2.88)		
$Par_{i,t-1}$ * (Different name)				0.91***	
				(2.70)	

$Par_{i,t-1}$ * (Indirectly linked)					0.86**
					(2.43)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	204,207	204,207	204,207	204,207	204,207
R^2	0.10	0.09	0.10	0.10	0.09

First, I test that the lower the parent firm investors' attention is, the more severe the lag in incorporating information into parent firm' s stock price will be, and thus the stronger the stock return predictability will be.

In Panel A of Table 3.1, the first three interaction terms are only weakly significant at 10% level. This supports that investors' limited attention to parent firms has limited explanatory power to subsidiary-parent return predictability. In the final column, I find that parent firm investors who have low attention to new ownership links can explain subsidiary-parent return predictability, since the interaction term is statistically significant at 1% level. These results are consistent with the inter-firm return predictability literature (e.g., Li et al., 2016; Lee et al., 2019; Ali and Hirshleifer, 2019).

In Panel B of Table 3.1, all five interaction terms are statistically significant at 5% level. These results indicate that parent firm investors' limited attention to foreign subsidiaries, different industrial subsidiaries, minor subsidiaries, different name subsidiaries, and indirectly linked subsidiaries are main reasons to the subsidiary-parent return predictability. These results are consistent with findings in Ginglinger et al. (2018).

Second, I test that the lower the subsidiary investors' attention is, the more severe the lag in incorporating information into subsidiary' s stock price will be, and thus the stronger the stock return predictability will be.

In Panel C of Table 3.1, Two of first three interaction terms are strongly significant with 1% level. This supports that comparing with parent firm investors, subsidiary investors have more lower attention to parent firms' links and information. The potential explanation is that investors are more likely to draw an accurate picture of a complex parent firm when they invest in the head of the group rather than in an entity within the firm network. In addition, as for listed subsidiaries' outside investors, the parent firm's value-relevant information, could be less informative as other subsidiaries' performances may blur that of the listed subsidiaries. In the final column, I find that subsidiary investors who have low attention to new ownership links can explain the parent-subsidiary return predictability, since the interaction term is statistically significant at 1% level. These results are consistent with the inter-firm return predictability literature (e.g., Li et al., 2016; Lee et al., 2019; Ali and Hirshleifer, 2019).

In Panel D of Table 3.1, all five interaction terms are statistically significant at 5% level. These results indicate that subsidiary investors' limited attention to foreign parent firms, different industrial parent firms, minor parent firms, different name parent firms, and indirectly linked parent firms are main reasons to the parent-subsidiary return predictability. These results are consistent with findings in Ginglinger et al. (2018).

In addition, I introduce a transparency shock (international cross-listing) to test whether the change of firm visibility (investors' attention) can impact return predictability. Baker et al. (2002) find that international firms can experience a significant transparency increase after listing their shares on two exchanges with a large number of international listings: the New York Stock Exchange (NYSE) and the London Stock Exchange (LSE). Each year, the NYSE provides a list of non-U.S. stocks listed on the NYSE and the LSE provides a list of non-U.K. securities listed on the LSE. I define that the listing firms in domestic markets of other 21 developed countries cross-list their shares in NYSE or LSE as international cross-listing examples in the sample. And then, I conduct a test of the mechanism of ownership-linked firms' returns forecast future returns of focal firm, by examining a particular setting where I can follow the same firm without international cross-listing and with international cross-listing. I restrict the analysis to solely those firms without international cross-listing that transition to with international cross-listing, through cross-listing their shares in NYSE or LSE. The advantage of this test is that I can now examine the time lags in information updating of the exact same firms when them without international cross-listing that transition to them with international cross-listing.

The sanity is that, when the firm has no international cross-listing, global investors (especially US and/or UK institutional investors) have lower attention to the firm. Therefore, its ownership-linked firms should have significant and positive predictability over its future returns. However, when the firm has international cross-listing, global investors (especially US and/or UK institutional investors) have higher attention to the firm. Therefore, its ownership-linked firms should be weaker predictors to its future return.

Table 3.2 International Cross-Listing and Firm Transparency

This table reports Fama-MacBeth forecasting regressions of stock returns in two subsamples. I identify all cases in which a firm without international cross-listing transitions into the firm with international cross-listing. I then include observations within three years prior to the status change in the firm without international cross-listing, and those within three years subsequent to the status change in the firm with international cross-listing. In columns (1) and (3), the dependent variable is the monthly return of the parent firm, the independent variable is the monthly return of the subsidiary; In columns (2) and (4), the dependent variable is the excess return of the subsidiary, the independent variable is the monthly return of the parent firm. Control variables are same as in Table 2.3 and are unreported for brevity. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

	Before international cross-listing		After international cross-listing	
	(1)	(2)	(3)	(4)
*100	Global	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Sub_{i,t-1}$	3.67** (2.38)			
$Par_{i,t-1}$		1.88*** (3.69)		
$Sub_{i,t-1}$			2.53* (1.87)	
$Par_{i,t-1}$				1.29** (2.36)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs.	3,416	6,126	3,416	6,126
R^2	0.10	0.08	0.08	0.06

I implement this test by identifying all cases in which a firm without international cross-listing transitions into a firm with international cross-listing. I then include observations within three years prior to the international cross-listing, and those within three years subsequent to the international cross-listing. I conduct Fama-MacBeth forecasting regressions and the results are reported in Table 3.2. When a firm has no international cross-listing, its predictor is statistically significant at less than or equal to 5% level. However, when that firm has international cross-listing, its predictor becomes the weaker significance level. This suggests that linked firms have larger predictive power before international cross-listing. After the international cross-listing, firms obtain higher international investors' attention. More international investors trade these mispriced stocks, so this mispricing effect becomes smaller and return predictability becomes weaker. These results are backed up with Baker et al. (2002).

3.4 The Limits to Arbitrage

3.4.1 Costs of Arbitrage

In a frictionless market, predictable stock returns should be arbitraged away. However, stock mispricing could not disappear thoroughly due to high costs of arbitrage. When stocks have higher costs of arbitrage, I should observe a stronger return predictability effect, since more sophisticated investors who have found these mispricing are unable to make arbitrage profits. Prior literature nominates two measures of costs of arbitrage in the stock market: idiosyncratic volatility and firm size. Cohen and Lou (2012) report that a strategy based on slow price adjustment to standalone firms' information is more pronounced for smaller firms and higher idiosyncratic volatility firms. Arbitrageurs' demand for a stock is inversely related to its arbitrage risk, which is reflected in its idiosyncratic volatility (Wurgler and Zhuravskaya, 2002). Baker and Wurgler (2006, 2007) argue that firms' cross-sectional sensitivity to market-wide sentiment is also a function of their idiosyncratic volatility. Short-sale constraints are one of the most important costs of arbitrage (e.g., Jones and Lamont, 2002; Lamont and Thaler, 2003; Nagel, 2005; Gromb and Vayanos, 2010). Trading costs are typically higher in the smaller firm stocks, and small firm stocks are difficult and costly to short (Israel and Moskowitz, 2013).

Idiosyncratic volatility (Idio Vol) is the standard deviation of the residuals from a regression of daily stock returns in the previous month on the Fama and French (1993) factors (at least ten daily returns required). Firm size (MktCap) is the market capitalization of the focal firm at the end of December in the previous calendar year. A dummy variable, $D_{i,t-1}$, is equal to one if the corresponding costs of arbitrage proxy (i.e., Idio Vol or MktCap) of focal firm i in the previous month is above the cross-sectional median of all firms. Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged subsidiaries' returns (or the lagged parent firms' returns) and the dummy variable ($D_{i,t-1}$).

Table 3.3: Costs of Arbitrage

This table reports that high costs of arbitrage to explain return predictability. In Panel A, the dependent variable is the monthly excess return of the parent firm and explanatory variables include the lagged subsidiaries' return ($Sub_{i,t-1}$) and the interaction term between the lagged subsidiaries' return ($Sub_{i,t-1}$) and the dummy variable. In Panel B, the dependent variable is the monthly excess return of the subsidiary and explanatory variables include the lagged parent firms' return ($Par_{i,t-1}$) and the interaction term between the lagged parent firms' return ($Par_{i,t-1}$) and the dummy variable. There are two proxy variables to measure costs of arbitrage. Idio Vol is the standard deviation of the residuals from a regression of daily stock returns in the previous month on the Fama and French (1993) factors (at least ten daily returns required). MktCap is the market capitalization of the focal firm at the end of December in previous calendar year. All interaction terms are based on dummy variables that take the value of one if the proxy variable is above the sample median in the previous month and zero otherwise. All regressions also include the dummy variable itself and lagged control variables. Control variables are same as in Table 2.3 and are unreported for brevity. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A: *Sub – Par*	(1)	(2)
*100	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$
$Sub_{i,t-1}$	8.53***	3.22***
	(3.14)	(2.87)
$Sub_{i,t-1}$ * (MktCap > Median)	-4.88***	
	(-3.18)	
$Sub_{i,t-1}$ * (Idio Vol > Median)		5.23***
		(3.35)
Country & Industry Fixed Effects	Yes	Yes
Controls	Yes	Yes
Obs.	113,851	113,851
R^2	0.12	0.12

Panel B: *Par – Sub*	(1)	(2)
*100	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$
$Par_{i,t-1}$	2.56***	1.04***
	(5.23)	(4.28)
$Par_{i,t-1}$ * (MktCap > Median)	-1.87***	
	(-3.21)	
$Par_{i,t-1}$ * (Idio Vol > Median)		1.53**
		(2.45)
Country & Industry Fixed Effects	Yes	Yes
Controls	Yes	Yes
Obs.	204,207	204,207
R^2	0.08	0.08

First, I test that the higher the parent firm's costs of arbitrage are, the more severe the lag in incorporating information into parent firm's stock price will be, and thus the stronger the stock return predictability will be.

As shown in Column 2 of Panel A, Table 3.3, the coefficient estimate on the interaction term between the idiosyncratic volatility dummy and $Sub_{i,t-1}$ is large and statistically significant, 5.23 (t-statistic = 3.35), which implies that the magnitude of the documented return effect is over 50% larger for stocks with high idiosyncratic volatility relative to those with low idiosyncratic volatility. This is consistent with my intuition that firms which are more probably to have large temporary stock price fluctuations, and are less magnetic to arbitrage capital, thus appear a stronger predictability effect. In the same vein, Column 1 of Panel A shows that, while the subsidiaries' return effect among large parent firms is strong and significant, the effect in small parent firms is even larger. Both findings support to the intuition that subsidiaries' information have even larger influence on high costs of arbitrage stocks. Although some investors could find this mispricing and return predictability, they still have difficulties and limitations to make the arbitrage due to high costs of arbitrage. These results are consistent with the literature (e.g., Cohen and Lou, 2012; Lee et al., 2019).

Second, I test that the higher the subsidiary's costs of arbitrage are, the more severe the lag in incorporating information into subsidiary's stock price will be, and thus the stronger the stock return predictability will be.

As shown in Column 2 of Panel B, Table 3.3, the coefficient estimate on the interaction term between the idiosyncratic volatility dummy and $Par_{i,t-1}$ is large and statistically significant, 1.53 (t-statistic = 2.45), which implies that the magnitude of the documented return effect is over 50% larger for stocks with high idiosyncratic volatility relative to those with low idiosyncratic volatility. This is consistent with my intuition that firms which are more probably to have large temporary stock price fluctuations, and are less magnetic to arbitrage capital, thus appear a stronger predictability effect. In the same vein, Column 1 of Panel B shows that, while the parent firms' return effect among large subsidiaries is strong and significant, the effect in small subsidiaries is even larger. Both findings support to the intuition that parent firms' information have even larger influence on high costs of arbitrage stocks. Although some investors could find this mispricing and return predictability, they still have difficulties and limitations to make the arbitrage due to high costs of arbitrage. These results are consistent with the literature (e.g., Cohen and Lou, 2012; Lee et al., 2019).

3.4.2 Difficult to Leverage with Borrowing Capital

There is a growing literature about the impact of funding liquidity on asset pricing. The stock market is not frictionless and arbitrageurs are constrained when there is a supply or demand shock on the capital. Duffie (2010) documents that when market friction exists, asset prices will not convert to the fundamental value immediately. Such shock may come from the difficulty to leverage with borrowing capital (Adrian et al., 2014). Akbas et al. (2015, 2016) find that hedge funds can better correct mispricing, when there are high capital inflows to hedge funds.

Following Adrian et al. (2014), I use broker-dealer capacity to measure the level of arbitrage capital and split the sample period into low and high funding liquidity periods. The broker-dealer quarterly leverage is defined as total financial asset / (total financial asset - total financial liability) by Adrian et al. (2014). The leverage factor is seasonally adjusted log changes in the level of broker-dealer leverage. The data are obtained from Table L.129 of the Federal Reserve.

Table 3.4: Difficult to Borrow Capital

This table reports the results for low and high securities broker-dealer's leverage in different periods. The broker-dealer's quarterly leverage is defined by Adrian et al. (2014) and obtained from Federal Reverse. I report the Fama and French (2018) six-factor alphas for the low funding liquidity period and high funding liquidity period. T-statistics are calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the

10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A: *Sub – Par*	(1)	(2)	(3)	(4)	(5)
Parent alphas	Global	Global ex USA	Asia-Pacific	Europe	North America
Low funding liquidity period	1.68***	1.72***	1.62***	2.23***	2.25***
High funding liquidity period	0.43**	0.45*	0.40*	0.70*	0.72*

Panel B: *Par – Sub*	(1)	(2)	(3)	(4)	(5)
Subsidiary alphas	Global	Global ex USA	Asia-Pacific	Europe	North America
Low funding liquidity period	1.50***	1.58***	2.71***	2.23***	1.30***
High funding liquidity period	0.44	0.48	0.94**	0.80*	0.45

In Table 3.4, I find that Fama and French (2018) six-factor abnormal returns are higher in low funding liquidity period than in high funding liquidity period. In low funding liquidity period, all strategy alphas are statically significant at 1% level. However, in high funding liquidity period, most strategy alphas are not statically significant at 5% level. These results indicate that difficult to leverage with borrow capital can explain return predictability. Although some investors could find this mispricing and return predictability, they still cannot make the arbitrage due to the difficulty to leverage with borrowing capital. These results are backed up with the Cao et al. (2019b).

3.5 The Opaque Internal Information of The Conglomerate

3.5.1 Internal Capital Markets

The investor response to information of linked firms may depend on the existence of internal capital markets whereby cash flow in one subsidiary are used to fund investment needs in another subsidiary. Stulz (1990) argues that a parent firm may overinvest in subsidiaries with limited investment opportunities. Meyer et al. (1992) state that a parent firm may subsidize one loss-making subsidiary by transferring funds from profitable subsidiaries. Lang and Stulz (1994) use market-to-book ratios (Tobin's Q) to measure the firm's investment opportunity. Berger and Ofek (1995) find that internal capital market activities, e.g., overinvestment and cross-subsidization, in a group decrease information processing efficiency and bring about value discounts. Lamont (1997) finds that investment in nonoil segments of petroleum companies decreases when cash flow in oil segments falls dramatically due to the large plunge of oil prices in 1985. This finding indicates that investment of one subsidiary in a parent firm may depends on the cash flows of other subsidiaries in a parent firm through internal capital market. Lamont and Polk (2001) find that firms with larger value discounts have higher subsequent returns than that with smaller value discounts. Therefore, I propose that active internal capital market may influence information processing efficiency and explain the return predictability.

Shin and Stulz (1998) investigate whether the internal capital market is active by establishing one model. They found that one segment's investment may be funded by other segments' cash flows through internal capital market. I use their methodology here to test whether the internal capital market is active.

Table 3.5: Internal Capital Markets

This table reports that internal capital markets' mechanisms. In Panel A, the dependent variable is the monthly excess return of the parent firm and explanatory variables include the lagged subsidiaries' return ($Sub_{i,t-1}$) and the interaction term between the lagged subsidiaries' return ($Sub_{i,t-1}$) and the dummy variable. In Panel B, the dependent variable is the monthly excess return of the subsidiary and explanatory variables include the lagged parent firms' return ($Par_{i,t-1}$) and the interaction term between the lagged parent firms' return ($Par_{i,t-1}$) and the dummy variable. I test each parent firm's (subsidiary's) active internal capital market at three different significance levels (1%, 5%, and 10%). The dummy variable is equal to one if the focal firm's internal capital market is active at different significance levels and zero otherwise. All regressions also include the dummy variable itself and lagged control variables. Control variables are same as in Table 2.3 and are unreported for brevity. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A: *Sub – Par*	(1)	(2)	(3)
*100	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Sub_{i,t-1}$	2.45***	2.36***	2.03***
	(3.35)	(3.23)	(2.73)
$Sub_{i,t-1}$ * (Active at 1% level)	2.88***		
	(2.93)		
$Sub_{i,t-1}$ * (Active at 5% level)		2.76***	
		(2.87)	
$Sub_{i,t-1}$ * (Active at 10% level)			2.38**
			(2.07)

Country & Industry Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Obs.	113,851	113,851	113,851
R^2	0.12	0.12	0.12

Panel B: *Par – Sub*	(1)	(2)	(3)
*100	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Par_{i,t-1}$	1.32***	1.14***	0.97***
	(5.23)	(4.35)	(4.02)
$Par_{i,t-1}$ * (Active at 1% level)	1.73**		
	(2.32)		
$Par_{i,t-1}$ * (Active at 5% level)		1.56**	
		(2.11)	
$Par_{i,t-1}$ * (Active at 10% level)			1.23*
			(1.83)
Country & Industry Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Obs.	204,207	204,207	204,207
R^2	0.08	0.08	0.08

I firstly examine subsidiary-parent return predictability. In this case, one parent firm has different subsidiaries. One subsidiary's investment can be influenced by cash flows of other subsidiaries in the parent firm. When the subsidiary announces positive cash flows, but even if the parent firm's investors are conscious of its ownership link and its other subsidiaries, parent firm's investors may be skeptical about whether it is a positive information to the parent firm. For example, cash flows of the subsidiaries may be expropriated to investments of one subsidiary with limited investment opportunities, resulting in overall unclear (negative or positive) information to the parent firm. Therefore, the hypothesis I are going to test is that, the more active of internal capital market of the parent firm is, the more severe the lag in incorporating information into parent firm's price will be, and thus the stronger the return predictability will be.

Shin and Stulz (1998) find that small subsidiaries in parent firms to benefit more from an efficient internal capital market because it would be easier for the internal capital market to fund subsidiaries with small capital expenditures relative to the firm's total investment budget. Therefore, I test the parent firm's smallest subsidiary's financing effect in the internal capital market.

For the smallest subsidiary i in parent firm j, I run time-series regression for 36 months. Only stocks which have complete ownership links over the 36-month are included in my analysis. I use Newey and West (1987)'s correction to calculate standard errors.

$$\frac{I_{i,j}(t)}{TA_j(t-1)} = \alpha + \beta_1 \frac{C_{not\ i,j}(t)}{TA_j(t-1)} + \beta_2 \frac{S_{i,j}(t-1) - S_{i,j}(t-2)}{S_{i,j}(t-2)} + \beta_3 \frac{C_{i,j}(t)}{TA_j(t-1)} + \beta_4 q_{i,j}(t-1) + \epsilon_{i,j}(t)$$

Where $I_{i,j}(t)$ denotes the gross investment of the subsidiary i of parent firm j in month t; $TA_j(t-1)$ is the book value of the total assets of firm j in month $t-1$; $C_{not\ i,j}(t)$ is the sum of the cash flow of the subsidiaries of parent firm j except for the cash flow of the subsidiary i in month t; $S_{i,j}(t-1)$ is the sales of subsidiary i of parent firm j in month $t-1$; $C_{i,j}(t)$

is the cash flow of subsidiary i of parent firm j in month t; $q_{i,j}(t-1)$ is Tobin's q for the subsidiary i of parent firm j in month $t-1$.

Following Shin and Stulz (1998), I define internal capital market as "active" if β_1 is significant at 1% level. I also study for alternative definition of "active" defined at significance of 5% and 10%, which give similar results. A dummy variable, $D_{i,t-1}$, is equal to one if the focal firm's internal capital market is active at different significance levels and zero otherwise. Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged subsidiaries' returns and the dummy variable ($D_{i,t-1}$).

Panel A of Table 3.5 reports Fama–MacBeth predictive regression with the dependent variable being a parent firm return ($Par_{i,t}$) in the following month. In addition to the interaction term between the dummy variable and $Sub_{i,t-1}$, the dummy variable itself and all control variables from the full specification are also included, which are unreported for brevity. The results are reported in columns 1 to 3 of Panel A, Table 3.5. Two of three interaction terms are statistically significant at 1% level and one of three interaction terms is statistically significant at 5% level. It indicates that active internal capital market decreases information processing efficiency and leads to the subsidiaries-parent return predictability. These results are supported by Berger and Ofek (1995).

In addition, I examine parent-subsidiary return predictability. In this case, one subsidiary has different parent firms. One subsidiary's investment can be influenced by its parent firms' other subsidiaries. When the loss-making subsidiary announces negative cash flows, but even if the subsidiary's investors are conscious of its ownership link and its parent firms, they could be still suspicious about whether this information is negative for the loss-making subsidiary. For example, cash flows of its parent firms' other subsidiaries may be expropriated to investments of the loss-making subsidiary, resulting in overall unclear (positive or negative) information to the subsidiary. Therefore, the hypothesis I are going to test is that, the more active of internal capital market of the subsidiary is, the more severe the lag in incorporating information into subsidiary's price will be, and thus the stronger the return predictability will be.

For the subsidiary i, I run time-series regression for 36 months. Only stocks which have complete ownership links over the 36-month are included in my analysis. I use Newey and West (1987)'s correction to calculate standard errors.

$$\frac{I_i(t)}{TA_i(t-1)} = \alpha + \beta_1 \frac{C_{not\ i,j}(t)}{TA_i(t-1)} + \beta_2 \frac{S_i(t-1) - S_i(t-2)}{S_i(t-2)} + \beta_3 \frac{C_i(t)}{TA_i(t-1)} + \beta_4 q_i(t-1) + \epsilon_i(t)$$

Where $I_i(t)$ denotes the gross investment of the subsidiary i in month t; $TA_i(t-1)$ is the book value of the total assets of subsidiary i in month $t-1$; $C_{not\ i,j}(t)$ is the sum of the cash flow of the other subsidiaries j of subsidiary i's parent firms in month t; $S_i(t-1)$ is the sales of subsidiary i in month $t-1$; $C_i(t)$ is the cash flow of subsidiary i in month t; $q_i(t-1)$ is Tobin's q for the subsidiary i in month $t-1$.

Following Shin and Stulz (1998), I define internal capital market as "active" if β_1 is significant at 1% level. I also study for alternative definition of "active" defined at significance of 5% and 10%, which give similar results. A dummy variable, $D_{i,t-1}$, is equal to one if the focal firm's internal capital market is active at different significance levels and zero otherwise. Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged parent firms' returns and the dummy variable ($D_{i,t-1}$).

Panel B of Table 3.5 reports Fama–MacBeth predictive regression with the dependent variable being a subsidiary return ($Sub_{i,t}$) in the following month. In addition to the interaction term between the dummy variable and $Par_{i,t-1}$, the dummy variable itself and all control variables from the full specification are also included, which are unreported for brevity. The results are reported in columns 1 to 3 of Panel B, Table 3.5. Two of three interaction terms are statistically significant at 5% level and one of three interaction terms is statistically significant at 10% level. It indicates that active internal capital market decreases information processing efficiency and leads to the parents-subsidiary return predictability. These results are supported by Berger and Ofek (1995).

3.5.2 Tunneling Effect

Fear of tunneling could be an alternative rationale. Focal firm's Investors fear rent extraction from that focal firm by other firms in the group (e.g., Johnson et al., 2000; Dyck and Zingales, 2004; Atanasov et al., 2010). I can explain the sanity as following: when the parent firm announces a positive information, but even if the subsidiary's investors are conscious of its ownership link and believe that the positive information of the parent firm result from the subsidiary, they could be still suspicious about whether this information is positive for the subsidiary. For example, the parent firm could extract earnings from the subsidiary by conducting self-dealing transactions at the expense of the subsidiary's investors. Therefore, positive information of parent firm level may result from expropriation decisions by the parent firm, resulting in negative information to the subsidiary.

Similarly, when the subsidiary announces a positive information, but even if the parent firm's investors are conscious of its ownership link and expect that the positive information of the subsidiary result from the parent firm or other subsidiaries in the group, they may be skeptical about whether the overall information is positive for the parent firm. For example, the subsidiary could extract earnings from other subsidiaries in a parent firm by conducting self-dealing transactions at the expense of other subsidiaries' investors. Therefore, positive information of the subsidiary may result from expropriation decisions from that subsidiary to other subsidiaries of a parent firm, resulting in overall negative information to the parent firm.

I use the Djankov et al. (2008) anti-self-dealing index[28] which estimates the legal protection of minority investors against expropriation and self-dealing and the Djankov et al. (2008) public enforcement index[29] which estimates the extent to which contracts are enforced in a court of law to measure one country's tunneling possibility.

Table 3.6: Tunneling Effect

This table reports that tunneling effect to explain return predictability. In panel A and B, for month t, I sort parent firm stocks into three groups based on the 20th and 80th percentiles of the sample distribution of each proxy measured for tunneling. Within each of the proxy group, I further sort parent firm stocks into three portfolios using the 20th and 80th breakpoints of lagged subsidiary stock returns ($Sub_{i,t-1}$). In panel C and D, for month t, I sort subsidiary

28 This index was downloaded at http://post.economics.harvard.edu/faculty/shleifer/data.html.
29 This index was downloaded at http://post.economics.harvard.edu/faculty/shleifer/data.html.

stocks into three groups based on the 20th and 80th percentiles of the sample distribution of each proxy measured for tunneling. Within each of the proxy group, I further sort subsidiary stocks into three portfolios using the 20th and 80th breakpoints of lagged parent firm stock returns ($Par_{i,t-1}$). T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A	Anti-self-dealing			
$Sub_{i,t-1}$	Low	Medium	High	High-Low
Low	0.10	0.38	0.41*	0.31
Medium	1.01*	0.54	0.47*	-0.54
High	1.56***	0.98*	0.57**	-0.99*
High - Low	1.46***	0.60*	0.16	-1.30**
	(2.74)	(1.86)	(0.62)	(-2.06)
FF6 alpha	1.43***	0.58*	0.13	-1.30**
	(2.78)	(1.87)	(0.51)	(-2.01)

Panel B	Public Enforcement			
$Sub_{i,t-1}$	Low	Medium	High	High-Low
Low	0.64*	0.48	-0.19	-0.83*
Medium	0.62*	0.72**	0.61	-0.01
High	0.80**	0.91**	1.43***	0.63*
High - Low	0.16	0.43	1.62***	1.46**
	(0.60)	(1.25)	(2.99)	(2.42)
FF6 alpha	0.17	0.35	1.47***	1.30**
	(0.74)	(1.18)	(3.05)	(2.28)

Panel C	Anti-self-dealing			
$Par_{i,t-1}$	Low	Medium	High	High-Low
Low	0.05	0.36	0.45	0.40
Medium	0.83*	0.76*	0.55*	-0.28
High	1.30***	0.86*	0.75**	-0.55*
High - Low	1.25***	0.50	0.30	-0.95*
	(3.62)	(1.56)	(0.87)	(-1.86)
FF6 alpha	1.30***	0.38	0.33	-0.98*
	(3.78)	(1.31)	(0.96)	(-1.73)

Panel D	Public Enforcement			
$Par_{i,t-1}$	Low	Medium	High	High-Low
Low	0.37	0.51	0.07	-0.30

Medium	0.36	0.70*	1.01*	0.65
High	0.49	1.05**	1.29*	0.80*
High - Low	0.12	0.54	1.22**	1.10*
	(0.36)	(1.58)	(2.42)	(1.93)
FF6 alpha	0.13	0.43	1.15**	1.02*
	(0.43)	(1.51)	(2.28)	(1.81)

In Table 3.6, I use anti-self-dealing index and public enforcement index to proxy for each country's tunneling possibility and split the all countries into high, medium, and low tunneling possibility countries. First, I test anti-self-dealing index and enforcement index to explain subsidiary-parent return predictability. In panel A, I find abnormal returns in low anti-self-dealing group are higher than that in high anti-self-dealing group. The alpha differences are statistically significant at 5% level. Also, in panel B, I find abnormal returns in high public enforcement group are higher than that in low public enforcement group. The alpha differences are statistically significant at 5% level. These results indicate that investors' fear of tunneling decreases information processing efficiency and leads to subsidiary-parent return predictability. These results are backed up with the literature (e.g., Johnson et al., 2000; Dyck and Zingales, 2004; Atanasov et al., 2010).

In addition, I test anti-self-dealing index and enforcement index to explain parent-subsidiary return predictability. In Panel C, I find excess returns in low anti-self-dealing group are higher than that in high anti-self-dealing group. The alpha differences are statistically significant at 10% level. Also, in panel D, I find excess returns in high public enforcement group are higher than that in low public enforcement group. The alpha differences are statistically significant at 10% level. These results indicate that investors' fear of tunneling decreases information processing efficiency and leads to parent-subsidiary return predictability. These results are backed up with the literature (e.g., Johnson et al., 2000; Dyck and Zingales, 2004; Atanasov et al., 2010).

3.6 The Information Complexity

Table 3.7: Information Complexity

This table reports information complexity to explain return predictability. In Panel A, the dependent variable is the monthly excess return of the parent firm and explanatory variables include the lagged subsidiaries' return ($Sub_{i,t-1}$) and the interaction term between the lagged subsidiaries' return ($Sub_{i,t-1}$) and the dummy variable. In Panel B, the dependent variable is the monthly excess return of the subsidiary and explanatory variables include the lagged parent firms' return ($Par_{i,t-1}$) and the interaction term between the lagged parent firms' return ($Par_{i,t-1}$) and the dummy variable. The information complexity proxies include subsidiaries' complexity index (SCI), parents' complexity index (PCI), analyst earnings one-year ahead forecast dispersion (Disp_1y), analyst earnings long-term growth forecast dispersion (Disp_Ltg), advertising expenses to market capitalization (Advertising/MktCap), and the number of employees to market capitalization (Employees/MktCap). I use these variables and construct the dummy variable that equals one if the focal firm is above the sample median and zero otherwise. All regressions also include the dummy variable itself and lagged control variables. Control variables are same as in Table 2.3 and are unreported for brevity. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A: *Sub – Par* *100	(1)	(2)	(3)	(4)	(5)
	Global	Global	Global	Global	Global

Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Sub_{i,t-1}$	9.12***	3.82***	3.29***	3.83***	3.24***
	(3.28)	(3.42)	(3.34)	(3.39)	(3.00)
$Sub_{i,t-1}$ * (SCI > Median)	-5.93***				
	(-3.05)				
$Sub_{i,t-1}$ * (Disp_1y > Median)		3.39***			
		(3.87)			
$Sub_{i,t-1}$ * (Disp_Ltg > Median)			3.01***		
			(3.54)		
$Sub_{i,t-1}$ * (Advertising/MktCap > Median)				3.49***	
				(3.57)	
$Sub_{i,t-1}$ * (Employees/MktCap > Median)					3.01**
					(2.54)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	113,851	113,851	113,851	113,851	113,851
R^2	0.13	0.13	0.13	0.12	0.12

Panel B: *Par – Sub* *100	(1)	(2)	(3)	(4)	(5)
	Global	Global	Global	Global	Global
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$Par_{i,t-1}$	2.54***	1.34***	1.21***	1.02***	1.48***
	(5.05)	(3.73)	(3.41)	(4.01)	(4.57)
$Par_{i,t-1}$ * (PCI > Median)	-1.34**				
	(-4.17)				
$Par_{i,t-1}$ * (Disp_1y > Median)		1.52**			
		(2.41)			
$Par_{i,t-1}$ * (Disp_Ltg > Median)			1.25**		
			(2.16)		
$Par_{i,t-1}$ * (Advertising/MktCap > Median)				1.68*	
				(1.94)	
$Par_{i,t-1}$ * (Employees/MktCap > Median)					1.93***
					(3.03)
Country & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	204,207	204,207	204,207	204,207	204,207
R^2	0.08	0.08	0.08	0.09	0.09

3.6.1 The Complexity of Ownership-Linked Firms

In this section, I examine the complexity of ownership-linked firms to influence the stock price updating of the focal firm in a certain extent. The more complex the ownership-linked firms are, the more stronger return predictability is. For example, Cohen and Lou (2012) find that the complexity of sales information drives the return predictability from easy-to-analyze firms to difficult-to-analyze firms.

First, I examine that the more complex the parent firm's subsidiaries are, the more severe the lag in incorporating information into parent firm stock price will be, and thus the stronger the stock return predictability will be. I design a subsidiary complexity index (SCI) to measure how the ownership complicates a parent firm according to a parent firm's segment ownerships. The SCI of parent firm i is constructed as:

$$SCI_i = \sum_j \left(\frac{ownership_{i,j}}{\sum_j ownership_{i,j}} \right)^2,$$

$$ownership_{i,j} = shareholding_{i,j} * market\ capitalization_j,$$

where $shareholding_{i,j}$ is the parent firm i's shareholding percentage to subsidiary j. $market\ capitalization_j$ is the market capitalization of subsidiary j. For instance, a parent firm *P* holds three subsidiaries *S1*, *S2*, *S3* with ownerships 40 million, 30 million, and 30 million, respectively. The subsidiary complexity index (SCI) for this parent firm *P* is conveyed as $(.4)^2 + (.3)^2 + (.3)^2 = 0.34$. The idea behind this measure is that the more dispersed a parent firm's subsidiaries are, the more complicated information needed to incorporate into parent firm's stock price is. A dummy variable, $D_{i,t-1}$, is equal to one if the subsidiary complexity index (SCI) of focal firm i in the previous month is above the cross-sectional median of all firms. Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged subsidiaries' returns and the dummy variable ($D_{i,t-1}$).

The results of the test are reported in Column 1 of Panel A, Table 3.7. The regression specification is similar to those in Table 2.3, i.e., a Fama-MacBeth predictive regression with the dependent variable being parent firm return ($RET_{i,t}$) in the following month. In addition to the interaction term between the dummy variable and $Sub_{i,t-1}$, the dummy variable itself along with all control variables from the full specification (Table 2.3, Panel A, Column 1) are also included, which are unreported for brevity. I observe from Column 1 that the coefficient estimate on the interaction term between an indicator of less complicated firms and past subsidiaries' return ($Sub_{i,t-1}$) is negative and statistically significant, -5.93 (t = -3.05). For comparison, the unconditional coefficient on $Sub_{i,t-1}$ is 9.12. Thus, consistent with the subsidiary complexity of parent firms driving the return predictability pattern, parent firms that are relatively less complicated, and so require simpler processing to incorporate information about any single ownership segment into prices, exhibit less pronounced predictable stock returns. The result indicates that investors have limited abilities to analyze complex subsidiaries' information and have delayed responses to complex subsidiaries' information. The investors' limited abilities to analyze complex information lead to the return predictability. It is consistent with the finding of Cohen and Lou (2012).

Second, I examine that the more complex the subsidiaries' parent firms are, the more severe the lag in incorporating information into subsidiary prices will be, and thus the stronger return predictability will be. I design the parent complexity index (PCI). The PCI of subsidiary i is constructed as:

$$PCI_i = \sum_j \left(\frac{shareholding_{i,j}}{\sum_j shareholding_{i,j}} \right)^2,$$

where $shareholding_{i,j}$ is subsidiary i's shareholding percentage hold by parent firm j. For instance, the subsidiary *S* has three parent firms *P1*, *P2*, *P3* with shareholding 20%, 30%, and 30%, respectively. The PCI for this subsidiary *S* is calculated as $(.25)^2 + (.375)^2 + (.375)^2 \approx 0.34$. The idea behind this measure is that the more dispersed subsidiaries' parent firms are, the more complicated the information needed to be incorporated into the subsidiary's stock price is. A dummy variable, $D_{i,t-1}$, is equal to one if the parent complexity index (PCI) of focal firm i in the previous month is above the cross-sectional median of all firms. Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged parent firms' returns and the dummy variable ($D_{i,t-1}$).

Column 1 of Panel B, Table 3.7 shows that the coefficient estimate on the interaction term between an indicator of less shareholding dispersed parent firms and past parent firms' return ($Par_{i,t-1}$) is negative and statistically significant at -1.34 ($t =$ -4.17). For comparison, the unconditional coefficient on $Par_{i,t-1}$ is 2.54. In line with the dispersed parent firms' value-relevant information of subsidiaries driving the return predictability pattern, subsidiaries' parent firms that are relatively less dispersed (thus require simpler processing of information about parent firms into subsidiary's stock prices) exhibit less pronounced predictable stock returns. The result indicates that investors have limited abilities to analyze complex parent firms' information and have delayed responses to complex parent firms' information. The investors' limited abilities to analyze complex information lead to the return predictability. It is consistent with the finding of Cohen and Lou (2012).

3.6.2 Analysts' Forecast Dispersion

In this section, I test whether analysts' forecast dispersion can explain return predictability. This test is motivated by findings in the behavioral finance literature. Chan et al. (1996) find that price continuation comes from a gradual response to information. Hirshleifer (2001) and Daniel et al. (1998, 2001) find that behavioral biases are increased when there is more complex information. Zhang (2006) proposes that behavioral biases are larger and price response is slower when there is larger analysts' forecast dispersion for the firm's value.

Following Zhang (2006), I use dispersion in analyst earnings one-year forward forecast and dispersion in analyst earnings long-term growth forecast to proxy information complexity. Dispersion in analyst earnings one-year forward forecast (Disp_1y) is calculated as the standard deviation of analyst earnings one-year forward forecasts scaled by the absolute value of the mean of the analyst earnings forecasts in the previous month. Dispersion in analyst earnings long-term growth forecast (Disp_Ltg) is calculated as the standard deviation of analyst earnings long-term growth forecast in the previous month.

I propose that firms which have higher analyst forecast dispersion will have larger information uncertainty and thus slower investors' responses.

First, I test that the more analysts' complexity the parent firms have, the more severe the lag in incorporating information into their prices will be, and thus the stronger the return predictability will be. A dummy variable, $D_{i,t-1}$, is equal to one if the corresponding analysts' complexity proxy (i.e., Disp_1y or Disp_Ltg) of focal firm i in the previous month is above the cross-sectional median of all firms. Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged subsidiaries' returns and the dummy variable ($D_{i,t-1}$).

Column 2 and 3 of Panel A, Table 3.7 show that the coefficient estimates on the interaction term between indicators of higher analyst forecast dispersion of parent firms and past subsidiaries' return ($Sub_{i,t-1}$) are positive and statistically significant. These results indicate that investors have limited abilities to deal with dispersed analysts' forecast information and have delayed responses to dispersed analysts' forecast information. The investors' limited abilities to deal with dispersed information lead to the return predictability. It is consistent with the finding of Zhang (2006).

Second, I test that the more analysts' complexity the subsidiaries have, the more severe the lag in incorporating information into their prices will be, and thus the stronger the return predictability will be. A dummy variable, $D_{i,t-1}$, is equal to one if the corresponding analysts' complexity proxy (i.e., Disp_1y or Disp_Ltg) of focal firm i in the previous month is above the cross-sectional median of all firms. Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged parent firms' returns and the dummy variable ($D_{i,t-1}$).

Column 2 and 3 of Panel B, Table 3.7 show that the coefficient estimate on the interaction term between indicators of higher analyst forecast dispersion of subsidiaries and past parent firms' return ($Par_{i,t-1}$) is positive and statistically significant. These results indicate that investors have limited abilities to deal with dispersed analysts' forecast information and have delayed responses to dispersed analysts' forecast information. The investors' limited abilities to deal with dispersed information lead to the return predictability. It is consistent with the finding of Zhang (2006).

3.6.3 Intangibles' Complexity

In this section, I examine whether intangibles' complexity can explain return predictability. Investors are difficult to value complex intangibles' firms. Morck and Yeung (1991) find evidence that the value discounts of the firm increase with growth of R&D and advertising expenses. Morck and Yeung (1992) find that multinational companies have a higher proportion of intangible assets than domestic companies, which are associated with higher returns. Hirshleifer et al. (2013) find that more technology-intensive firms are likely to be difficult to value, leading to a slower and potentially stronger information diffusion effect. The parent firms and subsidiaries which have more complex intangibles are more likely to be mispriced by investors.

Chan et al. (2001) examine whether stock prices fully value firms' intangible assets, specifically advertising expenses. Companies with high advertising expenses to equity market value earn large excess returns. Belo et al. (2014) find that more hiring rate firms have higher average stock returns than less hiring rate firms.

I consider these intangible variables in the literature, such as advertising expenses to market capitalization (Advertising/MktCap) and the number of employees to market capitalization (Employees/MktCap). I use these variables to measure focal firm's intangibles' complexity.

First, I test that the more intangibles the parent firms have, the more severe the lag in incorporating information into their prices will be, and thus the stronger the return predictability will be. A dummy variable, $D_{i,t-1}$, is equal to one if the corresponding intangible proxy (i.e., Advertising/MktCap or Employees/MktCap) of focal firm i in the previous month is above the cross-sectional median of all firms. Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged subsidiaries' returns and the dummy variable ($D_{i,t-1}$).

Column 4 of Panel A, Table 3.7 shows that the coefficient estimate on the interaction term between an indicator of more advertising expenses to market capitalization of parent firms and past subsidiaries' return ($Sub_{i,t-1}$) is positive and statistically significant at 3.49 (t-statistic = 3.57). For comparison, the unconditional coefficient on $Sub_{i,t-1}$ is 3.83. Column 5 of Panel A, Table 3.7 shows that the coefficient estimate on the interaction term between an indicator of more number of employees to market capitalization of parent firms and past subsidiaries' return ($Sub_{i,t-1}$) is positive and statistically significant at 3.01 (t-statistic = 2.54). These results indicate that investors have limited abilities to process complex intangibles' information and have delayed responses to complex intangibles' information. The investors' limited abilities to deal with complex intangibles' information lead to the return predictability. It is consistent with the literature (e.g., Chan et al., 2001; Hirshleifer et al., 2013; Belo et al., 2014).

Second, I test that the more intangibles the subsidiaries have, the more severe the lag in incorporating information into their prices will be, and thus the stronger the return predictability will be. A dummy variable, $D_{i,t-1}$, is equal to one if the corresponding intangible proxy (i.e., Advertising/MktCap or Employees/MktCap) of focal firm i in the previous month is above the cross-sectional median of all firms. Then Fama-MacBeth regressions are run by adding the dummy variable ($D_{i,t-1}$) and an interaction term between the lagged parent firms' returns and the dummy variable ($D_{i,t-1}$).

Column 4 of Panel B, Table 3.7 shows that the coefficient estimate on the interaction term between an indicator of more advertising expenses to market capitalization of subsidiaries and past parent firms' return ($Par_{i,t-1}$) is positive and statistically significant at 1.68 (t-statistic = 1.94). For comparison, the unconditional coefficient on $Par_{i,t-1}$ is 1.02. Column 5 of Panel B, Table 3.7 shows that the coefficient estimate on the interaction term between an indicator of more number of employees to market capitalization of subsidiaries and past parent firms' return ($Par_{i,t-1}$) is positive and statistically significant at 1.93 (t-statistic = 3.03). These results indicate that investors have limited abilities to process complex intangibles' information and have delayed responses to complex intangibles' information. The investors' limited abilities to deal with complex intangibles' information lead to the return predictability. It is consistent with the literature (e.g., Chan et al., 2001; Hirshleifer et al., 2013; Belo et al., 2014).

3.7 Comparison among mechanisms

My next step is to understand the relative importance of each of the above mechanisms which are potentially responsible for the return predictability. Following Augustin et al. (2019), I use the specifications within the setting of Fama-MacBeth regressions by adding interaction terms between the lagged subsidiaries' returns ($Sub_{i,t-1}$), or the lagged parent firms' returns ($Par_{i,t-1}$) and four dummy variables (D_1, D_2, D_3, and D_4) reflecting four competing mechanisms (investor attention, limits to arbitrage, opaque internal information, and information complexity, respectively) at a time, namely:

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,c,t} + \lambda_{2,d,t} + \lambda_{3,t}\, Sub_{i,t-1} + \lambda_{4,t}D_1 + \lambda_{5,t}Sub_{i,t-1} \times D_1 +$$

$$\lambda_{6,t}D_2 + \lambda_{7,t}Sub_{i,t-1} \times D_2 + \lambda_{8,t}D_3 + \lambda_{9,t}Sub_{i,t-1} \times D_3 + \lambda_{10,t}D_4 +$$

$$\lambda_{11,t}Sub_{i,t-1} \times D_4 + \lambda_{12,t}{}'\, X_{i,t-1} + \varepsilon_{i,t},$$

and

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,c,t} + \lambda_{2,d,t} + \lambda_{3,t}\, Par_{i,t-1} + \lambda_{4,t}D_1 + \lambda_{5,t}Par_{i,t-1} \times D_1 +$$

$$\lambda_{6,t}D_2 + \lambda_{7,t}Par_{i,t-1} \times D_2 + \lambda_{8,t}D_3 + \lambda_{9,t}Par_{i,t-1} \times D_3 + \lambda_{10,t}D_4 +$$

$$\lambda_{11,t}Par_{i,t-1} \times D_4 + \lambda_{12,t}{}'\, X_{i,t-1} + \varepsilon_{i,t},$$

I take a different approach to construct the mechanism measure. Instead of having a mechanism correspond to a single variable, I combine the information in multiple variables. For example, there are three variables (residual institutional ownership, turnover, and number of analysts) to proxy investor attention mechanism. Rather than construct a measure using firms' rankings on a single variable, such as turnover, I construct a composite measure (e.g., composite investor attention) by averaging rankings across multiple variables (e.g., residual institutional ownership, turnover, and number of analysts). By averaging, I aim to achieve a less noisy measure of each mechanism.

D_1 is a dummy variable, which is equal to one if the firm's composite investor attention characteristic (the average ranking of residual institutional ownership, turnover, and number of analysts) is above the median, and zero otherwise; D_2 is a dummy variable, which is equal to one if the firm's composite limits to arbitrage characteristic (the average ranking of small size (the inverse of the market capitalization) and idiosyncratic volatility) is above the median, and zero otherwise; D_3 is a dummy variable, which is equal to one if the firm's composite opaque internal information characteristic (active internal capital market at 1% significance level) is above the median, and zero otherwise. D_4 is a dummy variable, which is equal to one if the firm's composite information complexity characteristic (the average ranking of complexity index, analyst earnings one-year ahead forecast dispersion, analyst earnings long-term growth forecast dispersion, advertising expenses to market capitalization, and the number of employees to market capitalization) is above the median, and zero otherwise. All control variables and fixed effects are identical to those reported in Table 3.1.

Table 3.8: Comparison among mechanisms

This table compares four competing mechanisms of return predictability using Fama-MacBeth regressions by including interaction terms between the lagged subsidiaries' returns ($Sub_{i,t-1}$) or the lagged parent firms' returns ($Par_{i,t-1}$), and four dummy variables (D_1, D_2, D_3, and D_4) reflecting four competing mechanisms (investor attention, limits to arbitrage, the opaque internal information of the conglomerate, and information complexity) at a time, namely:

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,c,t} + \lambda_{2,d,t} + \lambda_{3,t} Sub_{i,t-1} + \lambda_{4,t} D_1 + \lambda_{5,t} Sub_{i,t-1} \times D_1 + \lambda_{6,t} D_2 + \lambda_{7,t} Sub_{i,t-1} \times D_2 + \lambda_{8,t} D_3 + \lambda_{9,t} Sub_{i,t-1} \times D_3 + \lambda_{10,t} D_4 + \lambda_{11,t} Sub_{i,t-1} \times D_4 + \lambda_{12,t}{}' X_{i,t-1} + \varepsilon_{i,t},$$

and

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,c,t} + \lambda_{2,d,t} + \lambda_{3,t} Par_{i,t-1} + \lambda_{4,t} D_1 + \lambda_{5,t} Par_{i,t-1} \times D_1 + \lambda_{6,t} D_2 + \lambda_{7,t} Par_{i,t-1} \times D_2 + \lambda_{8,t} D_3 + \lambda_{9,t} Par_{i,t-1} \times D_3 + \lambda_{10,t} D_4 + \lambda_{11,t} Par_{i,t-1} \times D_4 + \lambda_{12,t}{}' X_{i,t-1} + \varepsilon_{i,t},$$

An indicator D_1 equals one if the firm's composite investor attention characteristic (the average ranking of residual institutional ownership, turnover, and number of analysts) is above the median and zero otherwise; D_2 equals one if the firm's composite limits to arbitrage characteristic (the average ranking of small size (the inverse of the market capitalization) and idiosyncratic volatility) is above the median and zero otherwise; D_3 equals one if the firm's composite opaque internal information characteristic (active internal capital market at 1%

significance level) is above the median and zero otherwise. D_4 equals one if the firm's composite information complexity characteristic (the average ranking of complexity index, analyst earnings one-year ahead forecast dispersion, analyst earnings long-term growth forecast dispersion, advertising expenses to market capitalization, and the number of employees to market capitalization) is above the median and zero otherwise. I construct a composite measure (e.g., composite investor attention) by averaging rankings across multiple variables (e.g., residual institutional ownership, turnover, and number of analysts). By averaging, I aim to achieve a less noisy measure of each mechanism. All regressions also include the dummy variable itself and lagged control variables. All control variables and fixed effects are the same as in Table 3.1. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers parent firms and subsidiaries from twenty-three developed markets from January 2008 to December 2017.

Panel A: Sub-Par	
*100	*Global*
Dep Variable	$RET_{i,t}$
$Sub_{i,t-1}$	1.89***
	(2.65)
$Sub_{i,t-1}$ * (composite investor attention > Median)	-1.40
	(-0.69)
$Sub_{i,t-1}$ * (composite limits to arbitrage > Median)	1.73
	(1.24)
$Sub_{i,t-1}$ * (composite opaque internal information > Median)	2.53**
	(2.40)
$Sub_{i,t-1}$ * (composite information complexity > Median)	0.99
	(0.94)
Country & Industry Fixed Effects	Yes
Controls	Yes
Obs.	113,851
R^2	0.14

Panel B: Par-Sub	
*100	*Global*
Dep Variable	$RET_{i,t}$
$Par_{i,t-1}$	1.70***
	(2.98)
$Par_{i,t-1}$ * (composite investor attention > Median)	-0.78**
	(-2.26)
$Par_{i,t-1}$ * (composite limits to arbitrage > Median)	0.50
	(0.91)
$Par_{i,t-1}$ * (composite opaque internal information > Median)	0.57

	(0.86)
$Par_{i,t-1}$ * (composite information complexity > Median)	0.41
	(0.80)
Country & Industry Fixed Effects	Yes
Controls	Yes
Obs.	204,207
R^2	0.10

The test results are reported in Table 3.8. We report the estimates for the coefficients of four interaction terms. In Panel A, I compare four different mechanisms to explain the subsidiary-parent return predictability. I can see that the opaque internal information fully dominates the other three arguments in both economic and statistical terms. Other three arguments are subsumed by the opaque internal information. The interaction term between an indicator of more active internal capital market and past subsidiaries' return ($Sub_{i,t-1}$) is positive and statistically significant at 2.53 (t-statistic = 2.40). The other three interaction terms are not statistically significant. The results of Panel A show that the opaque internal information mechanism is the most important mechanism to explain subsidiary-parent return predictability.

In Panel B, I compare four different mechanisms to explain the parent-subsidiary return predictability. I can see that the investors' limited attention fully dominates the other three arguments in both economic and statistical terms. Other three arguments are subsumed by the investors' limited attention. The interaction term between an indicator of more investor attention and past parent firms' return ($Par_{i,t-1}$) is negative and statistically significant at -0.78 (t-statistic = -2.26). The other three interaction terms are not statistically significant. The results of Panel B show that the investors' limited attention mechanism is the most important mechanism to explain parent-subsidiary return predictability.

I will explain why the main mechanisms are different for subsidiary-parent return predictability and parent-subsidiary return predictability. First, why is the subsidiary-parent return predictability mainly driven by the opaque internal information (i.e., the internal capital market) rather than the investors' limited attention? The intuition is that many parent firms are important to the economy and the stock market and are usually followed by lots of analysts and media, so investors should not have low attention and high arbitrage costs to these high liquid parent firms' stocks. Panel A of Table 3.1 shows that three interaction terms of investors' limited attention are only weakly significant at 10% level. Cohen and Lou (2012) also find that investors' limited attention cannot explain the standalone-conglomerate return predictability, since many conglomerates are usually followed by lots of analysts and investors. They find that sales' information complexity is a new and the most prominent mechanism to drive the standalone-conglomerate return predictability. Similar with the conclusion of Cohen and Lou (2012), I find that investors' limited attention mechanism (statistically insignificant) is much weaker than the internal capital market information complexity mechanism (statistically significant) to explain the subsidiary-parent return predictability. The active but opaque internal capital market dramatically decreases the information processing efficiency inside the parent firm and mainly drives the subsidiary-parent return predictability.

Second, why is the parent-subsidiary return predictability mainly driven by the investors' limited attention rather than the opaque internal information (i.e., the internal capital market)? The intuition is that many subsidiaries (e.g., with low stock turnover, in different industries, and/or in foreign countries) are less followed by lots of industry analysts and local institutional investors, so these subsidiaries have low investors' attention. Panel C of Table 3.1 shows that two of three interaction terms of investors' limited attention are strongly significant with 1% level. The literature finds that the investors' limited attention is the most prominent mechanism to explain inter-firm return predictability (Cohen and Frazzini, 2008; Huang, 2015; Cao et al., 2016; Lee et al., 2019; Parsons et al., 2019; Ali and Hirshleifer, 2019). Another explanation is that investors are more likely to draw an accurate picture of a complex parent firm when they invest in the head of the group rather than in an entity within the firm network. As for subsidiaries' investors, the parent firm's information and other subsidiaries' information may blur information of the subsidiaries. Therefore, many investors may have less interest to pay attention to subsidiaries. Section 3.5.1 also implies that the internal capital market activities (e.g., overinvestment and cross-subsidization) between subsidiaries in one group is more active and significant than the internal capital market activities (e.g., overinvestment and cross-subsidization) between subsidiaries in different groups. It indicates that the internal capital market is the prominent mechanism to the subsidiary-parent return predictability rather than the parent-subsidiary return predictability.

3.8 Conclusion

In this chapter, I analyze which mechanisms can explain the return predictability along ownership links. I find four underlying mechanisms to explain the return predictability. These mechanisms include: (1) the investors' limited attention to focal firms, ownership links, or ownership-linked firms; (2) the limits to arbitrage, including high costs of arbitrage and difficult to leverage with borrowing capital; (3) the opaque internal information of the conglomerate, such as active internal capital market and tunneling effect; (4) the information complexity of focal firms or ownership-linked firms.

The contribution of this chapter is to find different mechanisms to explain the inter-firm return predictability in the ownership network. Besides traditional mechanisms (i.e., investors' limited attention and limits to arbitrage), I find that new mechanisms (i.e., the opaque internal information and information complexity) can also explain the inter-firm return predictability. The two new mechanisms have essential implications for behavioral finance models and theories. In addition, I find that the opaque internal information mechanism is the most important mechanism to explain subsidiary-parent return predictability and the investors' limited attention mechanism is the most important mechanism to explain parent-subsidiary return predictability. This chapter provides new perspectives to advance the understanding of the return predictability among the inter-firm networks.

CHAPTER 4 – Return Predictability in the Labor Competition Network based on Employee Satisfaction

4.1 Introduction

In the literature, there is no consensus on the relationship between employee satisfaction and firm value. In the traditional theory that focuses on the capital-intensive firms in the early 20th century, employees are treated as a homogeneous and low-skilled labor force (Taylor, 1991). To maximize profits, a firm minimizes labor costs; hence, improvement of employee satisfaction comes at the cost of firm profits. However, the revolution of firms and the market over the past century has dramatically changed the role of human capital in firm performance. Innovation, quality, and management efficiency – all of which are crucial factors of firm success – depend on human capital. Edmans (2011) and Edmans et al. (2017) provide empirical support to the human capital-centered theories of firms: employee satisfaction is found to be positively correlated with future firm value and stock returns. Green et al. (2019) find that firms with improved employee satisfaction significantly outperform firms with declines and conclude that employee reviews reveal fundamental firm information.

What follows from the above is that firms with similar employee satisfaction must share similar firm fundamentals. With investors' limited attention, firms with fundamental similarities or linkages exhibit momentum spillovers (Ali and Hirshleifer, 2019). Previous studies on limited attention and firm linkages have mainly focused on clear or contractual links among firms (e.g., Cohen and Frazzini, 2008; Lee et al., 2019). In contrast, the link investigated in the present study is implicit and less transparent. I focus on the implications of employee satisfaction similarity across firms on market price discovery and firms' stock returns.

According to the human relations theory, employee satisfaction could benefit firms via the following two non-mutually exclusive channels: motivation and retention. With regard to motivation, considering that employees are afraid to lose jobs they are satisfied with (Shapiro and Stiglitz, 1984), employee sanitization can motivate effort (Akerlof and Yellen, 1986). Furthermore, employees satisfied with their firm are likely to self-identify with it and, on internalizing their firm's goals, invest more effort into their work (McGregor, 1960). Consequently, firms with different levels of employee satisfaction are expected to show heterogeneous performance when they have to confront firm-specific shocks. For instance, during recessions, the firms with a relatively high level of employee satisfaction are more likely to demonstrate a better performance due to the high motivation of their employees.

Retention, which is the second channel through which employee satisfaction can benefit firms, is particularly important in knowledge-intense industries where employees are a key source of value creation (Edmans, 2011). The firms associated with a high level of employee satisfaction tend to be more attractive for talented workforce. Accordingly, many of the largest firms in the world, such as Amazon, Coca-Cola, GM, Johnson & Johnson, Microsoft, among others, attempt to retain employees (and thus improve employee satisfaction) by providing highly competitive salaries, rich and diverse employee benefits, and a transparent mechanism of employee promotion. Yet, firms' competition for employees is becoming increasingly fierce and transcends traditional industry- and state boundaries. For instance, IT firms are losing their technologists to quant hedge funds; robotics specialists are grabbed by not only engineering firms, but also by insurance, healthcare, and real-estate companies.[30] In a study based on job posting reports, Liu and Wu

[30] See https://news.efinancialcareers.com/us-en/292721/silicon-valley-losing-top-talent-to-quant-hedge-funds. Also, in its December 2, 2018 issue, *The Wall Street Journal* writes: "Some of the biggest recruiters of people with robotics expertise aren't just tech outfits or manufacturers, for instance, but also banks and real-estate firms. Auto makers and a slew of Silicon Valley firms are hiring autonomous-driving technicians, but so is insurance giant

(2018) find that the overlap between product market rivals and firm's labor competitors is less than 20%. As the competition for talents is not limited to the rivals within the same industry, a high level of employee satisfaction becomes a universal firm advantage.

Due to the differences in the level of retention of talented employees, firms with a lower employee satisfaction will suffer more when the industry or the entire economy experiences shocks. Therefore, in order to retain talented workers and to attract new workforce so that to maintain and improve firms' competitive positions, firms have to improve the satisfaction level of their employees.[31] Firms frequently learn from and interact with each other, which leads to consistent knowledge spillovers among firms (Jaffe et al., 1993). Since firms with similar employee satisfaction operate in the common labor competition network, they have peer effects on employee policies. Such externalities in corporate policies across firms have been well documented in recent studies. For instance, in a study on peer effects among product rivals in terms of the adoption of corporate social responsibility (CSR), Cao et al. (2019a) found that employee welfare policy, a key component of CSR, is also

Allstate Corp. And health-care company Johnson & Johnson has been recruiting experts in three-dimensional printing – touted as the next revolution in manufacturing – to develop customized orthopedics and surgical tools".

[31] According to *USA Today* from Sep. 16, 2015, even snacks may "lure employees to new companies: 48% of respondents said that if they were looking for a new job, they would weigh company perks, including availability of snacks, in their decision".

influenced by peer firms' decisions. Furthermore, Lee et al. (2019) show that predictable returns across firms sharing similar technology are driven by spillovers in technological innovation among these peer firms. If there are two firms in the labor market, whenever one firm implements a new employee welfare policy, the other firm may also implement a similar (or the same) policy to maintain its competitive advantage.[32] Owing to these peer effects on firms' employee policies, one can expect a high return predictability among firms with similar employee satisfaction.

In the present study, I investigate the level of employee satisfaction by using Glassdoor data – the largest career website that publishes, along with job postings for potential employees, company reviews written by former and current employees. The overall rating of a firm's employee satisfaction is based on the following five sub-categories: Culture & Values, Work/Life Balance, Senior Management, Compensation & Benefits, and Career Opportunities. Based on each firm's ratings on Glassdoor in June of the previous year, I obtain and rank top 1,000 listed firms (excluding financial

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[32] For example, in its August 6, 2018 issue, *The Wall Street Journal* writes: "General Motors Co. has struck a deal with a Detroit-based hospital system to offer a new coverage option to employees…in an attempt to lower costs and improve care… A smaller number of companies, including Walt Disney Co., Boeing Co., and Intel Corp. have taken the more-ambitious approach of having the health-care provider manage nearly all of the care of enrolled employees... GM is the latest of a growing list of employers that are choosing to negotiate their own terms with health-care providers…".

firms[33]) and test them for return predictability in the current year.[34] The predictor is defined as the distance- or equally-weighted measure of closeness of 20 neighbor firms (before and after the focal firm) with the employee satisfaction level similar to that of the focal firm.

I start by testing whether similar employee satisfaction firms are fundamentally linked to each other as discussed above. I find that the annual employment growth of the focal firm can be predicted by the annual employment growth of its similar employee satisfaction peer firms in the previous year. I also find that similar employee satisfaction partners' annual growth in revenues and profitability predict the focal firm's annual growth in revenues and profitability, respectively. This evidence of fundamental linkages uncovers the economic nature of firms with similar employee satisfaction levels.

Then, I empirically demonstrate a striking relation wherein the stock returns of the focal firms exhibit a predictable lag corresponding to the portfolio return of their respective peer firms with similar employee satisfaction. Focal firms with similar employee satisfaction firm peers that earn higher (lower) returns will

[33] Financial firms are often excluded in empirical asset pricing literature (e.g., Finke and Weigert, 2017, Lee et al., 2019) since the characteristics of accounting variables of financial firms are very different from firms operating in the real economy.
[34] Among all the US listed firms on Glassdoor, I focus on the top 1,000 listed firms with a high employee satisfaction, because human capital is less valuable in firms with a low employee satisfaction.

similarly earn higher (lower) returns in subsequent months. A trading strategy using a proxy based on the lagged monthly return of the distance-weighted similar employee satisfaction firm peers yields a monthly Fama and French (2018) six-factor alpha of 135 (value-weighted) and 179 (equally-weighted) basis points. Moreover, I observe a similar predictability with regard to each of the five sub-ratings of employee satisfaction. The results of cross-sectional regressions in the presence of various controls demonstrate that returns of similar employee satisfaction firms predict focal firms' returns.

I then conduct a number of tests to ensure that the predictive effect of similar employee satisfaction firms cannot be subsumed by the well-known industry momentum effect (Moskowitz and Grinblatt, 1999; Hou, 2007) and various inter-firm momentum effects, such as the focal firm's supplier and customer industry returns (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), the focal firm's "pseudo-conglomerate" firm peers' returns (Cohen and Lou, 2012), the focal firm's strategic alliance partners' returns (Cao et al., 2016), the focal firm's technological partners' returns (Lee et al., 2019), the focal firm's geographic (i.e., headquartered in the same city of U.S. 20 largest cities) peers' returns (Parsons et al., 2019), the focal firm's analyst (shared analyst coverage) peers' returns (Ali and Hirshleifer, 2019), the focal firm's subsidiaries' returns or parent firms' returns. Taken together, the results of all these tests convincingly demonstrate that the return predictability across similar employee satisfaction firms is distinct from the return predictability arising from industry linkages or other inter-firm connections.

I also test the return predictability between similar employee satisfaction firms internationally. To prevent a bias caused by a small number of multinational firms that are on the top employee satisfaction companies list of many countries, I use the top 1,000 listed firms (excluding financial ones) headquartered and primarily listed in Canada, France, Germany, and the UK. The results are mixed. In Canada and the UK, the returns of similar employee satisfaction firm peers predict focal firm's returns. However, in France and Germany, such return predictability is not observed. These results are consistent with those reported by Edmans et al. (2017) who find that employee satisfaction is associated with larger economic values only in more flexible labor markets (e.g., Canada, the UK, and the US). In these markets, since firms face lower hiring and firing constraints, and employees have a larger flexibility to respond to higher employee satisfaction, employee satisfaction can improve recruitment, retention, and motivation.

To better understand the mechanisms behind return predictability across similar employee satisfaction firms, I examine whether this predictability can be explained by investors' limited attention (proxied by firm turnover, analyst coverage, and residual institutional ownership), limits to arbitrage (proxied by firm size, idiosyncratic volatility, and funding liquidity), and/or information complexity (proxied by firm analysts' dispersion, and number of employees). Based on tests, my results show that, focal firms exhibit a slow price response largely due to lower investor attention, more difficult to arbitrage, and larger information complexity.

Next, in order to investigate the main reasons of the similar employee satisfaction firm peers' anomaly, I analyze the stock price reaction around earnings announcements. This setting is frequently used to test whether risk-based or mispricing factors can explain the existence of an anomalous return behavior (e.g., Bernard and Thomas 1989; La Porta et al., 1997; Gleason and Lee, 2003; Engelberg et al., 2018, Lee et al., 2019). Here, if a significantly larger part of the return anomaly is realized around earnings announcement days, then investors' misperceptions about a firm's future performance and cash flows (i.e., mispricing) become a candidate explanation of the phenomenon. Alternatively, without spikes in the return anomaly on earnings announcement days, a more likely driver is some risk factor. According to my results, similar employee satisfaction firm peers' anomaly spread is 800% larger on the earnings announcement days than on other days, suggesting that it is mispricing (rather than risk) that is the more likely driver of similar employee satisfaction firm predictability.

However, as argued by Lee and So (2015), return predictability can still be attributed to risk, even if the source of risk is unidentifiable. To test this possibility, I use an alternative approach to examine whether similar employee satisfaction firm predictability is consistent with a gradual diffusion of news relevant for a firm's future cash flows, rather than with a change in discount rate or risk. I analyze the impact of lagged returns of similar employee satisfaction firms on focal firm's standardized unexpected earnings (SUEs). This setting is not confounded by the possible existence of non-measurable risks. My results show that lagged returns of similar employee satisfaction firms can indeed predict SUEs, but with a decreasing predictive power over time that becomes insignificant after three quarters. This result provides further support to the conclusion that my return predictability pattern is unlikely to be related to risk.

The contribution of my results to the literature is two-fold. First, I add to the growing research on the impact of employee satisfaction on firm performance. As shown by Edmans (2011, 2012), the stock market does not promptly value intangibles, such as employee satisfaction. Furthermore, Green et al. (2019)

argue that employee satisfaction is the source of fundamental information about the firm. Psychological and sociological scholars found the reciprocal effect between employee satisfaction and own firm's performance (e.g., Weitz and Nuckols, 1955; Brayfield and Crockett, 1955; McGregor, 1960; Akerlof, 1982; Shapiro and Stiglitz, 1984; Akerlof and Yellen, 1986; Schneider et al., 2003). All these studies highlight the importance of employee satisfaction to their *own* firms. In contrast, I examine the impact of *other* firms with similar employee satisfaction on the focal firm's performance and find this relation to be distinct from other well-documented inter-firm links.

Second, I contribute to studies on inter-firm competition for employees. According to the extant strategy theory (Hall, 1993; Coff, 1997), human capital is a source of sustainable competitive advantage for firms. Furthermore, Yu and Cannella (2007) found that the theory of rivalry for employees is limited to the firms within the same industry. However, Markman et al. (2009) point out that the competition for employees goes beyond the boundaries of the same product market and the same industry. I find inter-firm return predictability based on employee satisfaction and provide new evidence on human capital competition that transcends industry boundaries.

My results have important implications to the study of return predictability from the implicit inter-firm networks. Current literature focuses on research of return predictability in the explicit inter-firm networks (e.g., Cohen and Frazzini, 2008; Ali and Hirshleifer, 2019). However, this chapter recommends further research to explore new return predictability from implicit and less transparent networks.

The remainder of the chapter is organized as follows. Section 4.2 describes the data and variables. Section 4.3 presents my main results on fundamental links and return predictability between employee satisfaction-linked firms. Section 4.4 analyzes underlying mechanisms. Section 4.5 rules out risk-based explanations by conducting both return-based and non-return-based tests. Section 4.6 concludes.

4.2 Data and Variables

I collect price, volume, and return data of US firms from the Center for Research in Security Prices (CRSP) and accounting information from Compustat. For non-US firms, I collect price, volume, and return data from Thomson Reuters Eikon and accounting information from Worldscope. I obtain time-varying Glassdoor ratings of top 1000 employee satisfaction ratings' listed firms (excluding financial firms) where are headquartered and primarily listed in the US market at the end of June each year, from 2009 (beginning year) to 2017 (end year). If two firms have same overall ratings, I compare their standard errors of five category ratings. The firm with small standard error of category ratings is ranked ahead of the firm with large standard error of category ratings. I use the Glassdoor firm ranking in June of year $y-1$ to test return predictability from January to December in year y.

Institutional ownership data and analyst coverage for all firms in the sample are obtained from Thomson Reuters Institutional Holdings (13F) and Thomson Reuters I/B/E/S, respectively. The sample period is from January 2010 to December 2018 with a total of 108 months. Following Fama and French (2012), I use the one-month US T-bill rate to calculate monthly excess returns.

The regressor of interest is lagged-one monthly returns of employee satisfaction-linked firm peers. It refers to as $ES_{i,t-1}$. $ES_{i,t-1}$ is constructed as the distance-weighted or equal-weighted portfolio returns of employee satisfaction-linked firm peers:

$$ES_{i,t-1} = \sum_{j\neq i} \frac{dis\_weight_{i,j,t-1}}{\sum_{j\neq i} dis\_weight_{i,j,t-1}} \cdot Ret_{j,t-1}$$

$$ES_{i,t-1} = \sum_{j \neq i} \frac{equ\_weight_{i,j,t-1}}{\sum_{j \neq i} equ\_weight_{i,j,t-1}} \cdot Ret_{j,t-1}$$

where $Ret_{j,t-1}$ is the stock returns of firm j in month $t-1$. $dis\_weight_{i,j,t-1}$ is a closeness measure between firm i and firm j in month $t-1$. For each firm, I use 20 neighbor firms before and after the firm to construct firm peer predictor. I use the distance-weighted portfolio of firm peers to forecast the focal firm's future returns. When firm i and firm j are ranked closer, the predictive effect from firm j to firm i is stronger. For example, if firm A, B, C, D, and E rank 1, 2, 3, 4, 5, I use two neighbor stocks to construct firm peer predictor. Firm C's predictor at time $t-1$ is defined as $ES_{C,t-1} = \frac{5-|3-1|}{14} \cdot Ret_{A,t-1} + \frac{5-|3-2|}{14} \cdot Ret_{B,t-1} + \frac{5-|3-4|}{14} \cdot Ret_{D,t-1} + \frac{5-|3-5|}{14} \cdot Ret_{E,t-1}$.

In contrast, $equ\_weight_{i,j,t-1}$ is an equal-weighted measure. For each firm, I use 20 neighbor firms before and after the firm to construct firm peer predictor. I use the equal-weighted portfolio of firm peers to forecast the focal firm's future returns. For example, if firm A, B, C, D, and E rank 1, 2, 3, 4, 5, I use two neighbor stocks to construct firm peer predictor. Firm C's predictor at time $t-1$ is defined as $ES_{C,t-1} = \frac{1}{4} \cdot Ret_{A,t-1} + \frac{1}{4} \cdot Ret_{B,t-1} + \frac{1}{4} \cdot Ret_{D,t-1} + \frac{1}{4} \cdot Ret_{E,t-1}$.

Table 4.1 shows the sample coverage and firm characteristics of the sample. In Panel A, I report the coverage of the sample as a fraction of the CRSP universe. The firms in the sample cover 65% of the CRSP common stock universe in terms of market capitalization, and 24% in terms of the total number of firms. The mean employee satisfaction-linked firms in the same industry and in same geographical location with the focal firm is 0.16 and 0.07, respectively.

In Panel B, I summarize the firm characteristics. Firms' mean *market capitalization ($ bln)* and *B/M* are 5.29 and 0.78 per month, respectively. Firm's mean Asset Growth (*AG*) and gross profitability (*GP*) are 0.23 and 0.42, respectively.

Table 4.1: Descriptive Statistics

This table presents summary statistics for sample coverage and firm characteristics. The US sample covers top 1000 employee satisfaction listed firms (excluding financial firms) based on time-varying Glassdoor firm ratings from January 2010 to December 2018. These firms are NYSE/NYSE MKT/NASDAQ-listed and their share codes are 10 or 11 that are contained in the CRSP/COMPUSTAT merged data file. Financial firms (with one-digit SIC code = 6) and stocks with price less than $5 at the end of previous year are excluded.

Panel A: Sample Coverage	Mean	Sd	Min	Med	Max
% of total number of stocks covered	0.24	0.03	0.23	0.25	0.27
% of total market capitalization covered	0.65	0.02	0.54	0.61	0.69
% linked stocks in same industry	0.16	0.11	0.02	0.12	0.77
% linked stocks in same geographic location	0.07	0.13	0.00	0.05	0.64

Panel B: Firm Characteristics	Mean	Sd	Min	Med	Max
Market Capitalization ($ bln)	5.29	9.40	0.65	4.33	47.62
B/M	0.78	1.16	0.04	0.52	5.17

AG	0.23	0.43	-0.73	0.21	0.99
GP	0.42	0.27	-0.96	0.40	1.07

4.3 Empirical Results

I next show the main results in this chapter. First, I verify whether employee satisfaction-linked firms are fundamentally related. Second, I show that return predictability is robust after controlling for a series of firm characteristics, industry momentum, and other inter-firm momentum. In addition, I show that return predictability is robust in different sub-periods and sub-samples. Finally, I report the international tests.

4.3.1 Fundamental Links

I test whether employee satisfaction-linked firms are fundamentally linked with each other. First, I regress focal firms' the growth of annual number of employees on the average growth measure of their employee satisfaction-linked firm peers. In addition, I regress focal firms' annual revenues and profitability growth on the average growth measures of their employee satisfaction-linked firm peers. I include year fixed effects and size and book-to-market as control variables in all regressions. For brevity, the coefficients on these controls are not reported in the table. For ease of interpretation, all independent variables are cross-sectionally standardized to have zero mean and unit variance.

Table 4.2: Fundamental Linkages

This table reports the results of panel regressions. *ES Employees' growth (t)* is calculated as the distance-weighted average employees' growth of employee satisfaction-linked firm peers. *ES Revenue growth (t)* is calculated as the distance-weighted average revenue growth of employee satisfaction-linked firm peers. *ES Profit growth (t)* is calculated as the distance-weighted average profit growth of employee satisfaction-linked firm peers. All variables are measured at the end of each calendar year and are winsorized at 1% and 99% levels. Independent variables are cross-sectionally standardized to have zero mean and unit variance. All regressions include year and industry fixed effects and size and book-to-market ratio as control variables. T-statistics based on standard errors clustered by year are shown below coefficient estimates. *** denote statistical significance at the 1% level. The sample covers firms from January 2010 to December 2018.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Variable	*Employees' growth (t)*	*Employees' growth (t+1)*	*Revenue growth (t)*	*Revenue growth (t+1)*	*Profit growth (t)*	*Profit growth (t+1)*
ES Employees' growth (t)	0.272***					
	(19.30)					
ES Employees' growth (t)		0.045***				
		(3.28)				
ES Revenue growth (t)			0.186***			
			(17.23)			
ES Revenue growth (t)				0.033***		
				(4.52)		
ES Profit growth (t)					0.047***	
					(16.18)	
ES Profit growth (t)						0.008***
						(4.21)

Year & Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	8640	7680	8,640	7,680	8,640	7,680
R^2	0.14	0.04	0.12	0.04	0.11	0.03

The results are shown in Table 4.2. In the first two columns of Table 4.2, the dependent variables are focal firm's current-year and one-year ahead number of employees' growth. The column 2 shows that distance-weighted employee satisfaction-linked firm peers' number of employees' growth can positively predict firm number of employees' growth. In column 3 and 4, the dependent variables become current-year and one-year ahead focal firm's revenues growth. The column 4 shows that distance-weighted employee satisfaction-linked firm peers' revenues growth can positively forecast firm revenues growth. In final two columns, the dependent variables are current-year and one-year ahead focal firm's profit growth. The result in column 6 shows that distance-weighted employee satisfaction-linked firm peers' profit growth is a strong predictor of future firm profit growth.

These results strongly justify that employee satisfaction-linked firms are fundamentally related. The evidence of fundamental linkages uncovers that the economic nature of firms with similar employee satisfaction level.

4.3.2 Univariate Portfolio Sorts

In this section, I design a trading strategy between employee satisfaction-linked firms. To conduct the test, I construct distance-weighted portfolio of employee satisfaction-linked firm peers and equal-weighted portfolio of employee satisfaction-linked firm peers as two predictors. According to the Glassdoor firm ranking in year $y-1$, I classify stocks into 5 quintiles. Quintile 1 focal firms have lowest employee satisfaction-linked firm peers' portfolio returns of lagged one-month. Quintile 5 focal firms have highest employee satisfaction-linked firm peers' portfolio returns of lagged one-month. Then, I calculate the value weighted and equal weighted portfolio returns of lowest and highest quintiles as well as the hedged portfolio returns of Quintile 5 minus Quintile 1 with corresponding statistical significance level.[35]

The Capital Asset Pricing Model (CAPM)[36] is unable to explain satisfactorily the cross-sectional stock returns (Fama and French, 1992; Jagannathan and Wang, 1996). Therefore, I use Fama and French's (2015) five-factor model and Fama and French's (2018) six-factor model to examine cross-sectional variation in alphas, since the cross-sectional variation in expected returns can be captured by these hedged style factors (*SMB*, *HML*, *RMW*, *CMA*, and *MOM*). If the hedged portfolio returns have high correlation with one hedged style factor returns, those hedged portfolio returns are absorbed or subsumed

[35] In order to adjust for serial correlation in monthly stock returns, I use Newey and West (1987) standard errors with three lags in the statistical tests.
[36] This is the static CAPM.

by the hedged style factor returns. In other words, that hedged portfolio (strategy) does not contribute abnormal returns (alphas).

Capital Asset Pricing Model (CAPM):

$$RET_i - R_f = \alpha_0 + \beta_1(Mkt - R_f) + \varepsilon_i,$$

Fama and French (2015) five-factor model:

$$RET_i - R_f = \alpha_0 + \beta_1(Mkt - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \varepsilon_i,$$

Fama and French (2018) six-factor model:

$$RET_i - R_f = \alpha_0 + \beta_1(Mkt - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \beta_6 MOM + \varepsilon_i,$$

Where:

Following Fama and French (1993, 2015, 2018), I define these risk factors in the thesis. $Mkt - R_f$, *SMB*, *HML*, *RMW*, *CMA*, and *MOM* include all NYSE, AMEX, and NASDAQ firms. Fama and French (1993, 2015, 2018) use the six value-weight portfolios formed on size and book-to-market, the six value-weight portfolios formed on size and operating profitability, the six value-weight portfolios formed on size and investment, and the six value-weight portfolios formed on size and prior (2-12) returns to construct *SMB*, *HML*, *RMW*, *CMA,* and *MOM* factors.

$Mkt - R_f$: the excess return of the market. $Mkt - R_f$ is the value-weight return of all CRSP firms minus the one-month Treasury bill rate.

SMB (Small Minus Big): the nine small stock portfolios' average return minus the nine big stock portfolios' average return.

$$SMB_{\left(\frac{B}{M}\right)} = \frac{1}{3}(Small\ Value\ +\ Small\ Neutral\ +\ Small\ Growth)$$
$$-\frac{1}{3}(Big\ Value\ +\ Big\ Neutral\ +\ Big\ Growth).$$
$$SMB_{(OP)} = \frac{1}{3}(Small\ Robust\ +\ Small\ Neutral\ +\ Small\ Weak)$$
$$-\ \frac{1}{3}\ (Big\ Robust\ +\ Big\ Neutral\ +\ Big\ Weak).$$
$$SMB_{(INV)} = \frac{1}{3}(Small\ Conservative\ +\ Small\ Neutral\ +\ Small\ Aggressive)$$
$$-\ \frac{1}{3}\ (Big\ Conservative\ +\ Big\ Neutral\ +\ Big\ Aggressive).$$
$$SMB = \frac{1}{3}\left(SMB_{\left(\frac{B}{M}\right)} +\ SMB_{(OP)} +\ SMB_{(INV)}\right).$$

HML (High Minus Low): the two value portfolios' average return minus the two growth portfolios' average return.

$$HML = \ \frac{1}{2}\ (Small\ Value + Big\ Value) - \ \frac{1}{2}\ (Small\ Growth + Big\ Growth).$$

RMW (Robust Minus Weak): the two robust operating profitability portfolios' average return minus the two weak operating profitability portfolios' average return.

$$RMW\ = \ \frac{1}{2}\ (Small\ Robust + Big\ Robust) - \ \frac{1}{2}\ (Small\ Weak + Big\ Weak).$$

CMA (Conservative Minus Aggressive): the two conservative investment portfolios' average return minus the two aggressive investment portfolios' average return;

$$CMA = \frac{1}{2}\,(Small\ Conservative + Big\ Conservative) - \frac{1}{2}\,(Small\ Aggressive + Big\ Aggresive).$$

MOM: the two high prior return portfolios' average return minus the two low prior return portfolios' average return.

$$MOM = \frac{1}{2}\,(Small\ High + Big\ High) - \frac{1}{2}\,(Small\ Low + Big\ Low).$$

Table 4.3 provides strong evidence that lagged returns of employee satisfaction-linked firm peers can forecast focal firm's stock returns. Panel A shows that monthly excess returns of focal firm stocks which have highest lagged one-month's returns of distance- or equal-weighted portfolio of employee satisfaction-linked firm peers have significantly higher monthly excess returns than those which have lowest lagged one-month's returns of distance- or equal-weighted portfolio of employee satisfaction-linked firm peers.

In Panel B and Panel C of Table 4.3, I report five-factor and six-factor abnormal returns of long-short focal firm portfolios based on distance- and equal-weighted portfolio of employee satisfaction-linked firm peers. The alpha results show the consistent results as excess returns of Panel A. The value- and equal-weighted long-short strategy based on lagged one-monthly return of distance-weighted portfolio of employee satisfaction-linked firm peers yields monthly Fama and French six-factor (2018) abnormal returns of 135 basis points ($t = 3.03$) and 179 basis points ($t = 3.64$). Overall, the results in Table 4.3 show that employee satisfaction-linked firm peers' lagged returns have predictive power to focal firm's future returns.

Table 4.3: Univariate Portfolio Sorts

This table reports the results of value- and equal-weighted univariate portfolio sorts of return predictability in labor competition network based on employee satisfaction. I use equal- and distance- weighted portfolio of employee satisfaction-linked firm peers to forecast the returns of focal firms. Panel A presents average excess returns for lowest and highest quintile portfolios and the 5-1 difference portfolio. Panel B reports abnormal returns for lowest and highest quintile portfolios and the 5-1 difference portfolio using the Fama and French (2015) five-factor model. Panel C reports abnormal returns for lowest and highest quintile portfolios and the 5-1 difference portfolio using the Fama and French (2018) six-factor model. The risk factors are downloaded from the webpage of Kenneth French. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with three lags. **, and *** denote statistical significance at the 5%, and 1% level, respectively. The sample covers firms from January 2010 to December 2018.

Panel A: Excess returns		
US	(1)	(2)
Value Weights	Equal	Distance
1 (Low)	-0.20	-0.21
5 (High)	0.82**	0.96**
5-1	1.02**	1.17***
	(2.43)	(2.70)
Equal Weights	Equal	Distance
1 (Low)	-0.08	-0.07
5 (High)	1.27***	1.49***

5-1	1.35***	1.56***
	(2.84)	(3.22)

Panel B: Fama and French (2015) five-factor alphas		
US	(1)	(2)
Value Weights	Equal	Distance
1 (Low)	-0.73*	-0.86*
5 (High)	0.50*	0.58*
5-1	1.23***	1.44***
	(2.81)	(3.19)
Equal Weights	Equal	Distance
1 (Low)	-0.90**	-1.08**
5 (High)	0.72*	0.83*
5-1	1.62***	1.91***
	(3.32)	(3.84)

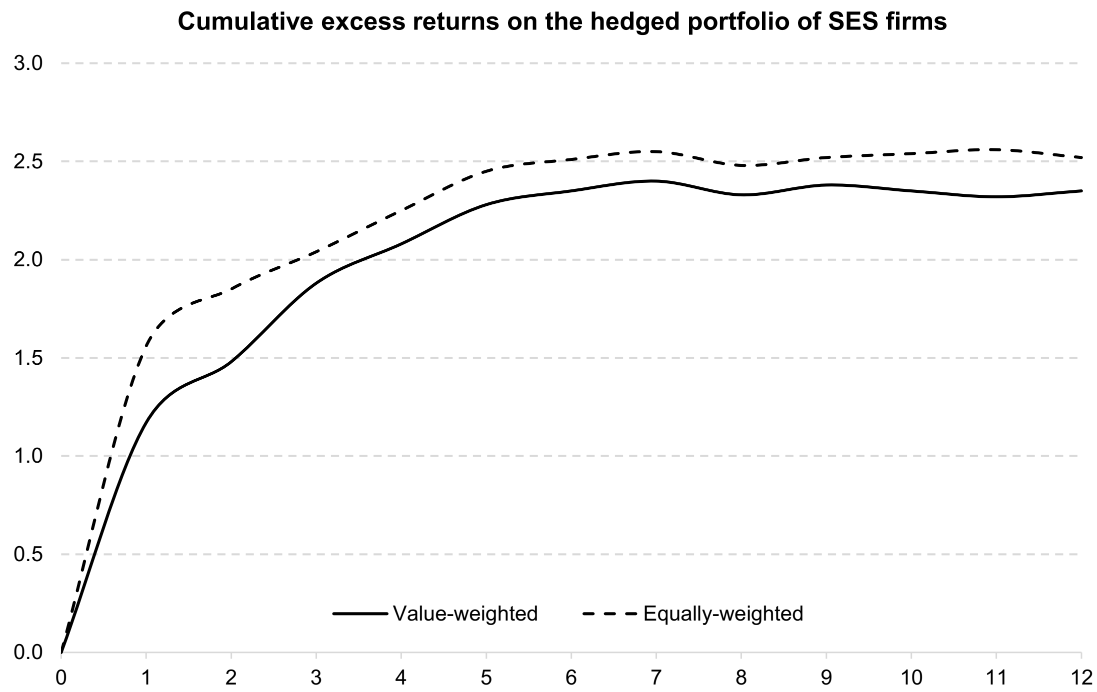
Panel C: Fama and French (2018) six-factor alphas		
US	(1)	(2)
Value Weights	Equal	Distance
1 (Low)	-0.67*	-0.79*
5 (High)	0.49	0.56
5-1	1.16***	1.35***
	(2.69)	(3.03)
Equal Weights	Equal	Distance
1 (Low)	-0.82**	-0.99**
5 (High)	0.70	0.80
5-1	1.53***	1.79***
	(3.17)	(3.64)

Furthermore, I also test the long-run return pattern of the predictive effect of firm peers with similar employee satisfaction. My aim here is to examine whether the documented strong return predictability effect represents an overreaction in focal firm information, in which case I should expect a reversal in the longer run. Alternatively, if similar employee satisfaction firm peers' information truly captures the focal firms' fundamental information, I should see no reversal.

To examine these two alternative explanations, I look at the cumulative excess returns (CERs) to the portfolio strategy over the 12-month period. In Figure 4.1, I depict these long-run CERs delivered by both value-weighted and equally-weighted portfolios. As can be seen in the figure, there is a significant upward drift in CERs over the first six months. The CERs flatten for the later months, showing no signs of reversal in the long run. These findings imply that the similar employee satisfaction firm predictability effect is not a simple overreaction to information. Rather, consistent with previous inter-firm return predictability studies (Cohen and Frazzini, 2008; Lee et al., 2019), my results reflect a delayed updating of focal firm prices to their fundamental values based on important information emanating from their similar employee satisfaction firm peers.

Figure 4.1: Long-run Cumulative Excess Returns

This figure shows cumulative excess returns (CERs) of the hedged similar employee satisfaction (SES) firm portfolio in the twelve months after portfolio formation. The sample period is from January 2010 to December 2018. At the beginning of each month, each focal firm is ranked in the ascending order based on the portfolio return of its peer firms with similar employee satisfaction at the end of the previous month. The portfolio of peer firms is based on [-20, +20] neighbor stocks for each focal firm. The ranked stocks are assigned into the five quintile portfolios. All stocks are value- (equal-) weighted within each portfolio, and the portfolios are rebalanced every month. The solid (dashed) line depicts the value-weighted (equally-weighted) CERs.



4.3.3 Cross-Sectional Regressions

In this section, I use Fama and MacBeth (1973) regressions to analyze whether the employee satisfaction-linked firms' return predictability remains robust after regulating the industry momentum and an array of different firm characteristics. Compared with other approaches (e.g., pooled OLS regressions) to deal with panel data, the Fama-MacBeth regressions take into account the cross-correlations and the serial correlation in the error term, so that the t-statistics are much more conservative (Choe et al., 2005). In addition, the Fama-MacBeth regressions are computationally simple to implement and are widely used in the literature of return predictability (Cochrane, 2005; Hou et al., 2018). The stock-level's Fama-MacBeth regression is made up of two steps. In the first step, I utilize the cross-sectional regression in each month as following:

$$RET_{i,t} - R_{f,t} = \lambda_{0,t} + \lambda_{1,d,t} + \lambda_{2,t}\, ES_{i,t-1} + \lambda_{3,t}{}'\, X_{i,t-1} + \varepsilon_{i,t},$$

where $RET_{i,t} - R_{f,t}$ is the excess return on focal firm's stock i in month t; $\lambda_{0,t}$ denotes the intercept; $\lambda_{1,d,t}$ industry-specific dummy variable which is equal to one if focal firm i is from industry d and zero otherwise; $ES_{i,t-1}$ is employee satisfaction-linked firms' stock return in month $t-1$; $X_{i,t-1}$ represents a vector of firm characteristics, including *Ln(Size)* the natural logarithm of the market capitalization measured in million dollars (Banz. 1981), *Ln(B/M)* the natural logarithm of book-to-market equity ratio (Basu, 1983), Mom the cumulative return of stock i from month $t-12\ to\ t-2$ (Jegadeesh and Titman, 1993), $RET_{i,t-1}$ the stock return of focal firm i in month $t-1$ (Jegadeesh, 1990; Lo and MacKinlay, 1990), *Turnover* the number of shares traded divided by the number of shares outstanding during a day, averaged over the past twelve months (Rouwenhorst, 1999; Ibbotson et al., 2013), Ind_mom the value-weighted two-digit SIC industry return of the focal firm in month $t-1$ (Grinblatt and Moskowitz, 1999; Nijman et al., 2004), asset growth (*AG*) the year-over-year growth rate of total assets (Cooper et al., 2008), gross profitability (*GP*) the revenue minus cost of goods sold scaled by assets (Novy-Marx, 2013), and best employee satisfaction companies (*BC*) to define as a 0-1 dummy variable that equals one if the focal firm is in the most recent top 100 employee satisfaction firm list and zero otherwise (Edmans, 2011).

The literature has found 452 forecasting variables to explain and predict the cross-sectional stock returns (Hou et al., 2018). However, I cannot use all of these forecasting variables as controls in my Fama-MacBeth regressions, since there is the serious overfitting problem (Han et al., 2018). I have to choose limited representative variables from different category of variables. For example, the book/market ratio is a representative variable of the “value” variables, since Fama and French (1993) find that the book/market ratio can explain the value effect and absorb the predictive power of other “value” variables (e.g., earnings/price, dividend yield, and cash flow/price). Hou et al. (2018) divide 452 anomalies/forecasting variables into six categories (value, momentum, investment, profitability, intangibles, and trading frictions). Therefore, I select some representative forecasting variables from six categories as controls. These control variables are also widely used in Fama-MacBeth regressions in other inter-firm return predictability papers (e.g., Cohen and Lou, 2012; Lee et al., 2019; Ali and Hirshleifer, 2019).

After the first step, I obtain the time-series coefficients for each explanatory variable. The second step is to verify whether the average coefficient estimates are statistically different from zero. Bali et al. (2016) document steps to calculate standard errors by using the Newey-West (1987) method. In the second step, I firstly calculate the mean of time-series coefficients for each explanatory variable. And then I regress the time-series coefficients on a vector of ones to obtain the time-series residuals for each explanatory variable. Thirdly, I input the time-series residuals and a vector of ones to the Newey and West (1987) adjustment to compute the standard errors to deal with heteroscedasticity and autocorrelation. Finally, the t-statistics are calculated by the mean of time-series coefficients divided by the standard errors. Table 4.4 reports the mean of time-series coefficients and the corresponding t-statistics.

The standard errors are computed using the Newey and West (1987) adjustment with 3 lags.[37] The choice of the lag length from 1 to 12 does not influence the significance of in any of my tests. The monthly return predictability literature believes that residuals are heteroskedastic and/or

[37] As the time between error terms increases, the correlation between the error terms decreases (Greene, 1997). Therefore, I use the Newey and West (1987) adjustment with 3 lags.

autocorrelated within one year (12 months). For example, Cohen and Lou (2012) use Newey and West (1987) adjustment with 12 lags to compute the standard errors. Li et al. (2016) use Newey and West (1987) adjustment with 6 lags to compute the standard errors.

Table 4.4: Cross-Sectional Regressions

This table reports the results of cross-sectional Fama and MacBeth (1973) forecasting regressions. The dependent variable is the excess return of the focal firm ($RET_{i,t}$), the risk-adjusted return of the focal firm ($RET_{i,t}^{adj6}$), or the industry-adjusted return of the focal firm ($RET_{i,t}^{ind}$). The risk-adjusted return of the focal firm is adjusted with respect to the Fama and French (2018) six-factor model. The industry-adjusted return of the focal firm is the focal firm's excess return over its value-weighted industry return ($Ind\_mom_{i,t}$). The explanatory variables include lagged one-monthly distance-weighted portfolio returns of employee satisfaction-linked firm peers ($ES_{i,t-1}$), firm size ($Ln(Size)$), book-to-market ratio ($Ln(B/M)$), focal firm's own lagged monthly return ($RET_{i,t-1}$), medium-term price momentum (Mom), asset growth (AG), gross profitability (GP), best 100 employee satisfaction companies (*BC*), stock turnover ($Turnover$), and focal firm's value-weighted industry return (Ind_mom). All explanatory variables are based on last non-missing available observation for each month t and are winsorized at 1% and 99% levels. Financial firms (with one-digit SIC code = 6) and stocks with price less than $5 at the end of previous year are excluded. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with three lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers firms from January 2010 to December 2018.

	(1)	(2)	(3)	(4)
*100	Excess	Excess	Risk-adjusted	Industry-adjusted
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}^{adj6}$	$RET_{i,t}^{ind}$
$ES_{i,t-1}$	7.28***	6.53***	5.22***	5.77***
	(4.63)	(4.26)	(3.52)	(3.87)
Ln(Size)		-1.25***	-0.52	-1.13***
		(-3.54)	(-1.45)	(-3.08)
Ln(B/M)		0.67**	0.27	0.60**
		(2.22)	(0.88)	(1.98)
$RET_{i,t-1}$		-3.86***	-3.09***	-3.46***
		(-3.15)	(-2.58)	(-2.81)
Mom		0.32	0.15	0.28
		(1.01)	(0.52)	(0.89)

AG		-2.10***	-0.83	-2.31***
		(-3.29)	(-1.36)	(-3.62)
GP		1.83*	0.74	1.56
		(1.74)	(0.70)	(1.49)
BC		2.58***	2.12***	2.35***
		(3.13)	(2.51)	(2.78)
Turnover		-0.32	-0.25	-0.29
		(-1.47)	(-1.18)	(-1.34)
Ind_mom		3.67***	2.93**	1.12
		(2.75)	(2.26)	(0.82)
Industry Fixed Effect	Yes	Yes	Yes	No
Obs.	103,680	103,680	103,680	103,680
R^2	0.08	0.11	0.04	0.03

Column 1 of Table 4.4 reports the results without control variables. I find that the distance-weighted portfolio returns of employee satisfaction-linked firm peers can predict the future returns of focal firms. The results demonstrate that the coefficient of $ES_{i,t-1}$ is statistically significant at 1% level. Column 2 reports the results with control variables. I find that the predictive power of employee satisfaction-linked firm peers cannot be subsumed by industry momentum and a series of firm characteristics. In column 3, I use risk-adjusted returns of focal firms, instead of excess returns, as the dependent variables. I compute risk-adjusted returns for focal firm i in month t as the difference between focal firm i's excess return and its expected factor returns based on the Fama and French (2018) six-factor models in month t: $RET_{i,t}^{adj6} = RET_{i,t} - R_{f,t} - \gamma_{i,1}Mkt_{i,t} - \gamma_{i,2}Smb_{i,t} - \gamma_{i,3}Hml_{i,t} - \gamma_{i,4}Rmw_{i,t} - \gamma_{i,5}Cma_{i,t} - \gamma_{i,6}Mom_{i,t}$, where $RET_{i,t}^{adj6}$ denote the six-factor risk-adjusted returns of focal firm i in month t, $\gamma_{i,p}$ is focal firm i's factor loading with respect to the different risk factors p $(p = 1,2, \dots ,6)$. To compute risk-adjusted returns, I use risk factors (Mkt, Smb, Hml, Rmw, Cma, Mom) from Ken French's webpage. Following Fama and French (1992) and Cao et al. (2016) I compute the factor loadings for each focal firm by using a time-series regression over the entire sample period.[38] I find that employee satisfaction-linked firm peers' lagged returns can significantly forecast risk-adjusted returns of focal firms. In the final column, I use industry-adjusted returns $(RET_{i,t} - R_{f,t} - Ind\_mom_{i,t})$ as the dependent variable. By subtracting industry return from the focal firm return, I eliminate any predictability arising from monthly industry-wide auto-correlation in returns. Column 4 shows the magnitude and significant level coefficient for $ES_{i,t-1}$ remains virtually the same when I use the industry-adjusted returns $(RET_{i,t} - R_{f,t} - Ind\_mom_{i,t})$ as the dependent variable.

Consistent with univariate portfolio sorts in Table 4.3, the results of Table 4.4 show that the portfolio return of employee satisfaction-linked firm peers can predict focal firm's return.

[38] I obtain similar results when I use rolling estimates.

4.3.4 Controlling for Other Inter-firm Links

In addition, I test whether the predictive power of employee satisfaction-linked firm peers cannot be subsumed by other inter-firm momentum. I test a series of inter-firm momentum variables. $Sup\_Ind_{i,t-1}$ and $Cus\_Ind_{i,t-1}$ are the supplier industry return and the customer industry return of focal firm i in the previous month (Menzly and Ozbas, 2010). $Cus_{i,t-1}$ is the customer return of focal firm i in the previous month (Cohen and Frazzini, 2008). $PC_{i,t-1}$ is the pseudo-conglomerate portfolio return of focal firm i in the previous month (Cohen and Lou, 2012). $SA_{i,t-1}$ is the strategic alliance partners' portfolio return of focal firm i in the previous month (Cao et al., 2016). $Tech_{i,t-1}$ is the technological partners' portfolio return of focal firm i in the previous month (Lee et al., 2019). $Geo_{i,t-1}$ is the average return of all other stocks headquartered in the same city of U.S. 20 largest cities in the previous month (Parsons et al., 2019). $CS_{i,t-1}$ is the weighted average return of stocks that are connected through shared analyst coverage in the previous month (Ali and Hirshleifer, 2019). $Sub_{i,t-1}$ is the ownership-weighted portfolio returns of subsidiaries of the focal firm i in the previous month. $Par_{i,t-1}$ is the control-weighted portfolio returns of parent firms of the focal firm i in the previous month. I also add control variables of Table 4.4 in all regressions. For brevity, these control variables are not reported.

Table 4.5: Controlling for Other Inter-firm Links

This table reports the results of cross-sectional Fama and MacBeth (1973) forecasting regressions. This table reports the excess return of focal firm i, $RET_{i,t}$ is regressed on the lagged one-monthly distance-weighted portfolio returns of employee satisfaction-linked firm peers ($ES_{i,t-1}$), inter-firm momentum ($Cus\_Ind_{i,t-1}$, $Sup\_Ind_{i,t-1}$, $Cus_{i,t-1}$, $PC_{i,t-1}$, $SA_{i,t-1}$, $Tech_{i,t-1}$, $Geo_{i,t-1}$, $CS_{i,t-1}$, $Sub_{i,t-1}$, or $Par_{i,t-1}$), and a vector of control variables, including industry momentum and firm characteristics in table 4.4. For brevity, coefficients of control variables in regressions are not reported. $Sup\_Ind_{i,t-1}$ and $Cus\_Ind_{i,t-1}$ are the supplier industry return and the customer industry return of focal firm i in the previous month (Menzly and Ozbas, 2010). $Cus_{i,t-1}$ is the customer return of focal firm i in the previous month (Cohen and Frazzini, 2008). $PC_{i,t-1}$ is the pseudo-conglomerate portfolio return of focal firm i in the previous month (Cohen and Lou, 2012). $SA_{i,t-1}$ is the strategic alliance partners' portfolio return of focal firm i in the previous month (Cao et al., 2016). $Tech_{i,t-1}$ is the technological partners' portfolio return of focal firm i in the previous month (Lee et al., 2019). $Geo_{i,t-1}$ is the average return of all other stocks headquartered in the same city of U.S. 20 largest cities in the previous month (Parsons et al., 2019). $CS_{i,t-1}$ is the weighted average return of stocks that are connected through shared analyst coverage in the previous month (Ali and Hirshleifer, 2019). $Sub_{i,t-1}$ is the ownership-weighted portfolio returns of subsidiaries of the focal firm i in the previous month. $Par_{i,t-1}$ is the control-weighted portfolio returns of parent firms of the focal firm i in the previous month. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with three lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers firms from January 2010 to December 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
*100	US	US	US	US	US	US	US	US	US	US	US	US	US
Dep Variable	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$	$RET_{i,t}$
$ES_{i,t-1}$	6.53***	5.68***	5.61***	5.49***	5.93***	6.28***	5.55***	5.34***	6.01***	5.09***	5.65***	5.24***	4.46***
	(4.26)	(3.81)	(3.77)	(3.68)	(3.87)	(4.04)	(3.63)	(3.49)	(3.92)	(3.32)	(3.68)	(3.43)	(2.87)
$Sup\_Ind_{i,t-1}$		1.29*		1.03									-0.36
		(1.78)		(1.45)									(-0.39)
$Cus\_Ind_{i,t-1}$			1.38**	0.91									1.16*
			(2.07)	(1.43)									(1.85)
$Cus_{i,t-1}$					2.33**								1.26

					(1.97)								(1.11)
$PC_{i,t-1}$						2.82**							1.38
						(2.03)							(1.01)
$SA_{i,t-1}$							0.84						0.74
							(1.15)						(1.03)
$Tech_{i,t-1}$								3.83**					1.90
								(2.08)					(1.01)
$Geo_{i,t-1}$									1.12*				0.90
									(1.90)				(1.51)
$CS_{i,t-1}$										4.36**			2.59
										(2.35)			(1.40)
$Sub_{i,t-1}$											2.28*		1.02
											(1.81)		(0.90)
$Par_{i,t-1}$												1.38**	0.61
												(2.05)	(1.02)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	103,680	98,169	98,169	98,169	8,147	24,362	14,469	35,579	96,494	70,097	31,114	20,746	5,832
R^2	0.11	0.11	0.11	0.11	0.12	0.12	0.11	0.11	0.12	0.12	0.12	0.12	0.14

Column 1 of Table 4.5 shows the original result as Column 2 of Table 4.4. Columns 2-12 show that the predictor $ES_{i,t-1}$ cannot be subsumed by other inter-firm links, such as supplier industry and customer industry returns, customer returns, 'pseudo-conglomerate' portfolio returns, alliance partners' returns, and technological partners' returns, geographic peers' returns, shared analyst coverage peers' returns, subsidiaries' returns, and parent firms' returns, respectively. In column 13, I find magnitude and significant level coefficient for $ES_{i,t-1}$ remains the similar after adding all these inter-firm variables. The coefficients of these inter-firm momentum variables become economically tiny and statistically insignificant.

To sum up, these results indicate that I find a new inter-firm predictor which cannot be explained by industry momentum, a series of firm characteristics, and other known inter-firm predictors.

4.3.5 Robustness

This section supplies additional analyses and stability checks to guarantee robustness for the main empirical results. I perform univariate portfolio sorts in different samples to reveal the results of different stability and robustness checks. Table 4.6 reports the results of diverse robustness checks.

Table 4.6: Robustness

This table presents robustness tests of the return predictability in labor competition network based on employee satisfaction. I report the Fama and French (2018) six-factor abnormal returns of value- and equal-weighted univariate portfolio sorts of focal firms in Panel A and B. Panel A performs abnormal returns for lowest and highest quintile portfolios and the 5-1 difference portfolio in different sub-periods, number of firm peers, and sub-samples. In Panel B, I perform univariate portfolio sorts in sub-ratings (Culture & Values, Work/Life Balance, Senior Management, Comp & Benefits, Career Opportunities). In panel C, I perform univariate portfolio sorts based on Burt and Hrdlicka (2019) adjustments. The risk factors are downloaded from the webpage of Kenneth French. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with three lags. **, and *** denote statistical significance at the 5%, and 1% level, respectively. The sample covers firms from January 2010 to December 2018.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
6-factor alphas	Time splits		# neighbor stocks		Industry		Location	
Value Weights	1st half	2nd half	10	30	Same	Different	Same	Different
1 (Low)	-0.87**	-0.70*	-0.77*	-0.81*	-0.84*	-0.73*	-0.93**	-0.64*
5 (High)	0.62*	0.49	0.54	0.58	0.59	0.52	0.66*	0.45
5-1	1.49***	1.19***	1.31***	1.39***	1.43***	1.26***	1.59***	1.09**
	(3.27)	(2.74)	(2.96)	(3.10)	(3.18)	(2.86)	(3.47)	(2.57)
Equal Weights	1st half	2nd half	10	30	Same	Different	Same	Different
1 (Low)	-1.09**	-0.87*	-0.96**	-1.02**	-1.05**	-0.92*	-1.17**	-0.80*
5 (High)	0.87*	0.72	0.78*	0.82*	0.84*	0.75	0.93*	0.67
5-1	1.96***	1.59***	1.74***	1.84***	1.89***	1.67***	2.10***	1.47***
	(3.94)	(3.27)	(3.55)	(3.73)	(3.82)	(3.42)	(4.18)	(3.06)

Panel B	(1)	(2)	(3)	(4)	(5)
	6-factor alphas				

Value Weights	Culture & Values	Work/Life Balance	Senior Management	Comp & Benefits	Career Opportunities
1 (Low)	-0.66	-0.69	-0.73*	-0.89**	-0.77*
5 (High)	0.46	0.49	0.52	0.63*	0.54
5-1	1.12***	1.18***	1.26***	1.53***	1.31***
	(2.62)	(2.71)	(2.86)	(3.35)	(2.96)
Equal Weights	Culture & Values	Work/Life Balance	Senior Management	Comp & Benefits	Career Opportunities
1 (Low)	-0.81*	-0.85*	-0.92*	-1.12**	-0.97**
5 (High)	0.67	0.70	0.75	0.90*	0.79*
5-1	1.48***	1.56***	1.67***	2.02***	1.76***
	(3.08)	(3.22)	(3.42)	(4.06)	(3.59)

Panel C	(1)	(2)	(3)
Burt and Hrdlicka (2019)	Excess returns	5-factor alphas	6-factor alphas
Value Weights			
1 (Low)	-0.19	-0.79*	-0.73*
5 (High)	0.88**	0.53	0.52
5-1	1.08**	1.33***	1.25***
	(2.54)	(2.99)	(2.84)
Equal Weights			
1 (Low)	-0.06	-0.97**	-0.89**
5 (High)	1.35***	0.75	0.73
5-1	1.42***	1.72***	1.62***
	(2.96)	(3.52)	(3.34)

In Panel A, I test the return predictability in different sub-samples and sub-periods. First, In the first sub-period from January 2010 to June 2014, the value- and equal-weighted portfolio alphas are 1.49% and 1.96%, respectively. In the second sub-period from July 2014 to December 2018, the value- and equal-weighted portfolio alphas are 1.19% and 1.59%, respectively. The four alphas are statistically significant at 1% level. Second, I test the return predictability by using different number of neighbor stocks. I find that choice of number of neighbor stocks does not influence the return predictability, which eliminates the data mining concerns to firm peers. The alphas are similar with results in Table 4.3. In addition, I also divide firm peers based on industry and geographic location. Both same industry firm peers and different industry firm peers can generate statistically significant alphas. Same industry firm peers can generate larger abnormal returns than different industry firm peers. Also, both same location firm peers and different location firm peers can generate statistically significant alphas. Same location firm peers can generate larger abnormal returns than different location firm peers. These results show that information diffusion and cross-learning between employee satisfaction-linked firms are not constrained in the same industry and location but exceed the boundary of industry and location.

In Panel B, I present the abnormal returns (i.e., six-factor alphas) based on each of the five sub-ratings respectively: Culture & Values, Work/Life Balance, Senior Management, Compensations & Benefits, and Career Opportunities. As I expected, the alphas are statistically significant in all five sub-ratings, confirming the unanimous existence of information diffusion and cross-learning on different factors among employee satisfaction-linked firms. In particular, the alpha based on Compensations & Benefits is the largest among all five cases, which suggests that the effect of the information diffusion and cross-learning (between employee satisfaction-linked firms) on Compensations & Benefits is the strongest among the five factors. This is consistent with the intuition that the compensation level (or other benefits) of a firm is objective and thus easier to verify and learned by firm peers than other factors (such as culture and work/life balance which are subjective). For example, if Facebook increases the salary level of its engineers, Google may want to follow up soon enough so that not to lose its existing engineers and maintain its firm competitiveness.

Burt and Hrdlicka (2019) identify the correlation (correlated alphas) between economic linked firms. For example, this correlation makes sorting on customers' returns or alphas an implicit sort on the alphas of their suppliers. Burt and Hrdlicka (2019) suggest one correction method by subtracting the predicted returns of asset pricing model from the sorting return. Following their method, I use employee satisfaction-linked firms' idiosyncratic return instead of their raw returns to construct predictors. I use the daily returns of each employee satisfaction-linked firm over the previous twelve months to calculate its alphas and factor loadings to the Fama and French (2018) six-factor model. Then I obtain each employee satisfaction-linked firm's idiosyncratic return by using factor coefficient estimates and factor returns.

Panel C reports the portfolio returns when I use each firm's idiosyncratic returns rather than raw returns to construct employee satisfaction -linked predictor. The results are consistent with Table 4.3, when I remove the correlated alphas. The lagged idiosyncratic returns of employee satisfaction-linked firms can forecast stock returns of focal firms. These results reveal that the information drawn out from the raw returns of the employee satisfaction-linked firms is mostly orthogonal to the firms' common exposure to asset pricing factor returns.

4.3.6 International Tests

In this section, I test the return predictability in international samples. I want to verify whether the return predictability between employee satisfaction-linked firms is unified or mixed in flexible and rigid labor markets. The international samples include top 1000 employee satisfaction firms (excluding financial firms) that are both headquartered and primarily listed in Canada, France, Germany, and UK, respectively, to prevent my results being driven by a small number of multinational firms that are on the top employee satisfaction companies list of many countries. The dependent variable is the excess return of the focal firm, the risk-adjusted return of the focal firm, or the industry-adjusted return of the focal firm.

Table 4.7: International Tests

This table reports the international samples of cross-sectional Fama and MacBeth (1973) forecasting regressions. The international samples include top 1000 employee satisfaction firms (excluding financial firms) that are both headquartered and primarily listed in Canada, France, Germany, and UK, respectively, to prevent my results being driven by a small number of multinational firms that are on the top employee satisfaction companies list of many countries. The dependent variable is the excess return of the focal firm ($RET_{i,t}$), the risk-adjusted return of the focal firm ($RET_{i,t}^{adj6}$), or the industry-adjusted return of the focal firm ($RET_{i,t}^{ind}$). The risk-adjusted return of the focal firm is adjusted with respect to the Fama and French (2018) six-factor model. The industry-adjusted return of the focal firm is the focal firm's excess return over its value-weighted industry return ($Ind\_mom_{i,t}$). The explanatory variables include lagged one-monthly distance-weighted portfolio returns of employee satisfaction-linked firm peers ($ES_{i,t-1}$), firm size ($Ln(Size)$), book-to-market ratio ($Ln(B/M)$), focal firm's own lagged monthly return ($RET_{i,t-1}$), medium-term price momentum (Mom), asset growth (AG), gross profitability (GP), best 100 employee satisfaction companies (*BC*), stock turnover ($Turnover$), and focal firm's value-weighted industry return (Ind_mom). All explanatory variables are based on last non-missing available observation for each month t and are winsorized at 1% and 99% levels. Financial firms (with one-digit SIC code = 6) and stocks with price less than $5 at the end of previous year are excluded. I report only the coefficient on $ES_{i,t-1}$ for brevity. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with three lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers firms from January 2010 to December 2018.

Country	(1)	(2)	(3)

*100	Excess	Risk-adjusted	Industry-adjusted
Dep Variable	$RET_{i,t}$	$RET_{i,t}^{adj6}$	$RET_{i,t}^{ind}$
Canada	3.58***	2.94***	3.29***
	(3.17)	(2.60)	(2.92)
France	-1.34	-1.07	-1.21
	(-0.97)	(-0.78)	(-0.87)
Germany	-0.83	-0.64	-0.71
	(-1.04)	(-0.80)	(-0.88)
UK	2.75**	2.28**	2.48**
	(2.38)	(1.98)	(2.14)

The results are reported in Table 4.7. I find that return predictability between employee satisfaction-linked firms exists in flexible labor market, such as Canada and the UK. However, the return predictability disappears in rigid labor market, such as France and Germany. The results indicate that return predictability depends on a country's labor market flexibility. The return predictability and information diffusion between employee-satisfaction-linked firms in the US are not anomalous in a global context. The return predictability exists only in countries with high labor market flexibility. These results are consistent with findings in Edmans et al. (2017). They find that investing in high employee satisfaction firms can generate abnormal returns only in countries with high labor market flexibility.

4.4 Underlying Mechanism

In this section, I shed light on which underlying mechanisms can explain the employee satisfaction-linked firms' return predictability. To explore the possible underlying mechanisms of the main results, I study the bivariate portfolio sorts to various firm characteristics associated with the extent of investors' limited attention, limits to arbitrage, and information complexity.

Table 4.8: Mechanisms

This table reports the interactions between employee satisfaction-linked firm peers' past return and proxies for different mechanisms. Each month, stocks are sorted on each proxy into two groups, and then independently sorted on firm peers' past return into quintiles. I calculate the long/short Fama and French (2018) six-factor alphas in each group and alpha differences between two groups. There are three variables to proxy limited attention, including turnover, residual institutional ownership, and analyst coverage. Turnover is the focal firm's turnover measured as the average daily turnover in the prior year. Analyst Coverage is the number of analysts covering the focal firm at the end of the previous month. Res Inst Own is institutional ownership of the parent firm orthogonalized with regard to firm size at the end of December. There are three variables to proxy limits to arbitrage, including firm size, idiosyncratic volatility, and funding liquidity period. Size is the log value of market capitalization of focal firm at the end of the previous month. IdioVol is the standard error of the residuals from a regression of daily stocks returns in the previous month on the Fama and French (1993) three-factor model. Funding liquidity period is divided into low liquidity period and high liquidity period based on broker-dealer's quarterly leverage that is defined by Adrian et al. (2014) and obtained from Federal Reverse. There are two variables to proxy information complexity, including analysts' forecast dispersion and number of employees. Analysts' forecast dispersion is analyst earnings one-year ahead forecast dispersion at the end of the previous month. Number of employees is the focal firm's number of employees at the end of the previous month. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with three lags. **, and *** denote statistical significance at the 5%, and 1% level, respectively. The sample covers firms from January 2010 to December 2018.

Panel A: Investors' limited attention			
US	(1)	(2)	(3)
Value Weights	Turnover	# Analysts	Res Inst Own
High	0.54	0.61	0.57

Low	2.16***	2.09***	2.13***
H-L	-1.62***	-1.49***	-1.57***
	(-3.42)	(-3.17)	(-3.32)
Equal Weights	Turnover	# Analysts	Res Inst Own
High	0.62	0.70	0.65
Low	2.70***	2.62***	2.67***
H-L	-2.08***	-1.92***	-2.01***
	(-4.24)	(-3.95)	(-4.13)

Panel B: Limits to arbitrage

US	(1)	(2)	(3)
Value Weights	MktCap	Idio Vol	Funding liquidity
High	0.59	1.90***	0.77
Low	2.11***	0.80*	1.93***
H-L	-1.51***	1.10**	-1.16***
	(-3.22)	(2.49)	(-2.59)
Equal Weights	MktCap	Idio Vol	Funding liquidity
High	0.68	2.38***	0.88
Low	2.63***	0.92*	2.41***
H-L	-1.95***	1.46***	-1.53***
	(-4.01)	(3.13)	(-3.25)

Panel C: Information complexity

US	(1)	(2)
Value Weights	Analysts' forecast dispersion	# employees
Low	0.72	0.69
High	1.90***	2.01***
H-L	1.18***	1.32***
	(2.61)	(2.88)
Equal Weights	Analysts' forecast dispersion	# employees
Low	0.82	0.79
High	2.28***	2.51***
H-L	1.46***	1.72***
	(3.13)	(3.60)

4.4.1 Investors' Limited Attention

If the predictive power of firm peers with similar employee satisfaction is related to investors' inattention, I should expect a stronger effect for firms with less investor attention. I use the following three investor inattention measures in the literature: stock turnover, analyst coverage, and residual institutional ownership. I predict that firms with a lower stock turnover, analyst coverage, and residual institutional ownership will show a more sluggish stock price reaction to the information from firm peers with similar employee satisfaction. Turnover is the focal firm's turnover measured as the average daily turnover in the previous year. The analyst coverage is defined as the number of analysts following the focal firm in the previous year from the IBES database. I use the residual institutional ownership, which is the institutional ownership of the parent firm orthogonalized with regard to firm size at the end of December of each year.

Each month, stocks are sorted on each proxy into two groups, and then independently sorted on firm peers' past return into quintiles. I calculate the long/short Fama and French (2018) six-factor alphas in each group and alpha differences between two groups.

Panel A in Table 4.8 show the alpha differences between high attention and low attention groups. I find that alpha differences are statistically significant at 1% level. The results broadly support my ideas that the return effect is driven by investors' limited attention.

4.4.2 Limits to Arbitrage

I also expect to see a stronger return effect for the firm stocks with more binding arbitrage costs, since investors are unable to freely trade and fully update these firms' stock prices (Hirshleifer et al., 2011; Beneish et al., 2015). I use the following three proxies for the limits to arbitrage: MktCap, Idio Vol, and funding illiquidity. MktCap is the log value of market capitalization of the focal firm at the end of the previous month. Idio Vol is the idiosyncratic volatility – the standard error of the residuals from a regression of daily stocks returns in the previous month based on the Fama and French (1993) three-factor model. Finally, as defined in Adrian et al. (2014), funding liquidity period is divided into low liquidity and high liquidity periods based on the broker-dealer's quarterly leverage and is obtained from the Federal Reverse.

Panel B of Table 4.8 reports the results. I find that alpha differences between high limits to arbitrage and low limits to arbitrage groups are statistically significant at 1% level. The results support to my hypothesis that return effect is stronger for the stocks with higher limits to arbitrage.

4.4.3 Information Complexity

The firms which have larger information complexity could generate larger return predictability effect, since investors who have limited abilities to analyze the complicated information are unable to fully update these firms' stock prices (i.e., Cohen and Lou, 2012; Huang, 2015). There are two proxies to test information complexity, including analysts' forecast dispersion and number of employees. Analysts' forecast dispersion is analyst earnings one-year ahead forecast dispersion at the end of the previous month. Number of employees is the focal firm's number of employees at the end of the previous month.

Panel C of Table 4.8 reports the results. I find that alpha differences between high information complexity and low information complexity groups are statistically significant at 1% level. The results support to my hypothesis that return effect is stronger for the stocks with larger information complexity.

4.5 Risk or Mispricing

From above sections I find that although the return predictability between employee satisfaction-linked firms cannot be explained by asset pricing factors, they are possibly driven by some unobserved risks. For example, if employee satisfaction-linked firms can proxy for changes in discounts rates of focal firms, which would change expected returns of focal firms. In this section, I shed light on whether risk or mispricing drives the return predictability.

4.5.1 Earnings Announcements

In this part, I examine if the return effect could be driven by unobserved risks. In the previous part, the observed return predictability between firms with similar employee satisfaction cannot be explained by the standard asset pricing factors. However, this predictability could still be driven by some unobserved risks. Indeed, I have previously shown that the six risk factors from the Fama French (2018) model, along with the industry momentum factor, cannot explain my results. However, other possible factors, such as the ones related to the focal firm's discount rate, could also affect the firm's expected return. Following Bernard and Thomas (1989), Chopra et al. (1992), Lee et al. (2019), and others, I examine how stock price reacts around the subsequent earning announcements. The intuition behind this approach is that, if the anomaly is explained by changes in underlying risks, then the stock returns should smoothly adjust over subsequent periods. However, if the anomaly is related to mispricing, I should expect a stronger anomaly manifestation during the earnings announcement window, as the earnings' release helps to correct investors' prior expectation errors on firms' future cash flows.

Following Engelberg et al. (2018) and Lee et al. (2019), I conduct the test based a simple regression analysis. In this regression model, the dependent variable is the daily return of the focal firm's stock instead of its monthly return, while independent variables are the similar employee satisfaction peer firm portfolio return, a dummy for an earnings announcement window (*EDAY*), as well as the interaction term consisting of these two variables. Control variables include the lagged values of the focal firm's stock returns, stock returns squared, and its trading volume over the past 10 days.

Table 4.9: Earnings Announcements

This table reports regressions of announcement window daily returns (*Daily Ret*) on day-fixed effects, the *ES* variable, earnings day dummy variables, and lagged control variables. For brevity, control variables' coefficients are not reported. *ES* is the distance-weighted portfolio return of employee satisfaction-linked firm peers in the previous month. An earnings announcement is defined as the one-day or three-day window centered on an earnings release, e.g., days $t-1$, t, and $t+1$. *EDAY* is a dummy variable and equals to 1 if that daily observation is during an announcement window, and zero otherwise. Following Engelberg et al. (2018), I collect earnings announcement dates from the Compustat quarterly database, testing the firm's trading volume scaled by market trading volume for the day before, the day of, and the day after the reported earnings announcement date, and define the day with the highest volume as the earnings announcement day. Control variables are lagged values for each of the past ten days for stock returns, stock returns squared, and trading volume.

Standard errors are clustered on time. T-statistics are shown in parentheses, coefficients marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers firms from January 2010 to December 2018.

	One-day window	*Three-day window*
Dep Variable	*Daily Ret*	*Daily Ret*
ES	0.004**	0.005***
	(2.54)	(2.59)
*ES * EDAY*	0.032***	0.002***
	(4.83)	(7.48)
EDAY	0.002***	0.002***
	(6.97)	(3.44)
Lagged Controls	Yes	Yes
Day Fixed Effects	Yes	Yes
Obs.	3,218,240	3,218,240
R^2	0.13	0.13

Table 4.9 summarizes the estimation results. In column (1), the earnings announcement window is defined for one day only, while in column (2) – over three days. According to the mispricing explanation, I expect larger returns to the similar employee satisfaction firm strategy during the earnings announcement window. However, contrary to this expectation, for one-day earnings announcement window, the ES coefficient is 0.004, but the $ES \times EDAY$ interaction coefficient is 0.032. Said differently, the return spread based on the hedged similar employee satisfaction firm strategy is more than eight times larger during the earnings news release. For the three-day earning announcement window, the results show a similar pattern. Therefore, the results in Table 4.9 suggest that standard risk models are unlikely to explain the similar employee satisfaction firm portfolio return effect.

4.5.2 Forecasting Standardized Unexpected Earnings

Lee and So (2015) show that anomaly return can still be attributed to risk, even if the source of risk has not been identifiable or measurable. Accordingly, in what follows, I test whether firms with similar employee satisfaction have a predictive power to standardized unexpected earnings (SUEs) of focal firms. Since SUEs can capture unanticipated changes in the focal firm's earnings and are not return-based, the results of this test are not confounded by imperfect controls of risks. Furthermore, given that SUEs are also fundamental determinants of future cash flows of firms, the results of this test can further confirm whether the anomaly return is due to the changes of unexpected cash flows, instead of a risk compensation effect.

To test the focal firms' future earnings predictability, I use the Fama-MacBeth regressions. Specifically, I examine whether similar employee satisfaction firm peers' returns can predict the focal firm's SUEs. The dependent variable is the unexpected earnings scaled by the standard deviation of unexpected earnings over eight past quarters, SUE.[39] The independent variable is the lagged by one quarter return of similar employee satisfaction firm peers computed from

[39] Unexpected earnings measure is the year-over-year change in quarterly earnings before extraordinary items.

the preceding three months. I also add the focal firm's own lagged $SUEs$ (up to four quarters) as control variables. The dependent variable is winsorized at 1% and 99% in the cross-section, while all explanatory variables are scaled from 0 to 1 according to the assignment in deciles. For consistency, I restrict sample firms to those that have fiscal quarters ending in March, June, September, and December.

Table 4.10: Forecasting Standardized Unexpected Earnings

This table reports cross-sectional Fama-MacBeth regressions of future standardized unexpected earnings (SUEs), defined as unexpected earnings (year-over-year change in quarterly earnings before extraordinary items) scaled by the standard deviation of unexpected earnings over the eight preceding quarters. The predictor (ES) is calculated based on past three-month returns of employee satisfaction-linked firm peers. The dependent variable is winsorized at 1% and 99% in the cross-section, and all the explanatory variables are assigned to deciles and scaled to range from 0 to 1. For consistency, the sample is restricted to firms with fiscal quarters ending in March, June, September, and December. I run Fama-MacBeth regressions with industry fixed effects. This table reports regressions of future SUE from the next four fiscal quarters on the predictor (ES). I add 1-quarter to 4-quarter lags of the firm's own SUEs as control variables. T-statistics are shown in parentheses and calculated using Newey-West (1987) method with four lags. T-statistics are shown in parentheses, coefficients marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers firms from January 2010 to December 2018.

	(1)	(2)	(3)	(4)
*100	*Quarter1*	*Quarter2*	*Quarter3*	*Quarter4*
Dep Variable	$SUE_{i,t}$	$SUE_{i,t+1}$	$SUE_{i,t+2}$	$SUE_{i,t+3}$
$ES_{i,t-1}$	10.35***	7.26***	4.14**	0.93
	(5.16)	(3.62)	(2.01)	(0.54)
Lagged $SUEs$ (4 quarters)	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
Obs. (quarters)	36	36	36	36
R^2	0.23	0.23	0.23	0.23

Table 4.10 shows the test results with unexpected earnings predictability over four subsequent future fiscal quarters; that is, the dependent variable, SUE, is estimated for quarters t to $t+3$. As can be seen from the table, the coefficients on the lagged returns of similar employee satisfaction peer firms are positive, but significantly decrease from the first to the fourth fiscal quarter. The forecasting pattern decays over time. These results provide further support to my conclusion that return predictability between firms with similar employee satisfaction is consistent with a gradual information diffusion of cash flows, instead of changes in underlying risk.

4.6 Conclusion

In this chapter, I report evidence of return predictability of among U.S. firms with similar employee satisfaction by using a novel firm-ranking data based on employee satisfaction reviews from Glassdoor. I show that the lagged returns of firm peers with similar employee satisfaction can predict focal firm's returns. This effect is distinct from industry and other known inter-firm momentum strategies and is not subsumed by the standard risk-factor models. I also illustrate that investors' limited attention, the limits to arbitrage, and information complexity could explain the underreaction to information from firms with similar employee satisfaction. In addition, the results of my tests on similar employee satisfaction firm return predictability in four other countries are largely consistent with those reported by Edmans et al. (2017). I also find that, while this predictability phenomenon is present in the flexible labor markets, such as those of Canada and the UK, it is not observed in the rigid labor markets of France and Germany.

In order to examine whether the abnormal returns based on the information from firms with similar employee satisfaction are explained by the unobserved risk factors or investors' mispricing, I use two different methods. Specifically, I test whether the lagged returns of firm peers with similar employee satisfaction (i) have a similar predictability effect on focal firms' returns both on the earning announcements days and in other periods, and (ii) predict focal firms' standardized unexpected earnings in the long-run over several quarters. The results of both tests indicate that my documented return predictability pattern cannot be explained by risk.

The results of this study make two contributions to the literature. First, I add to the growing research on the impact of employees' perception of well-being in their companies on their own firm performance, thus adding to such studies as Edmans (2011, 2012), Edmans et al. (2017) and Green et al. (2019). However, unlike previous studies, I examine the impact of *other* firms with similar employee satisfaction on a given firm's performance, and show that this relation is distinct from known inter-firm predictability effects. Second, since my findings on the inter-firm return predictability within a group of companies with similar employee satisfaction provide new evidence on cross-industry human capital competition, my results also contribute to the body of work on inter-firm competition for employees (e.g., Yu and Cannella, 2007; Markman et al., 2009).

The results of this chapter have essential implications to the study of return predictability from the implicit inter-firm networks. Current literature focuses on research of return predictability in explicit inter-firm networks (e.g., Cohen and Frazzini, 2008; Ali and Hirshleifer, 2019). However, this chapter advises further research and future directions to exploit new return predictability from implicit and less transparent networks.

CHAPTER 5 – Conclusion and Implication

5.1 Conclusion

This thesis has provided new evidence and findings on inter-firm return predictability. Cohen and Frazzini (2008) propose that firms do not exist as independent entities, but are linked to each other through various relationships. Some links are clear and contractual, but some links are implicit and less transparent. In this thesis, I contribute to a new explicit inter-firm link, the ownership link, and a new implicit inter-firm link, the employee satisfaction link. I find return predictability along ownership links and return predictability across employee satisfaction links. My research has important implications for the return predictability and pricing factor literature. In the literature of return predictability, a large number of predictors constructed by the focal firm's own information or own characteristics have been digested by popular factors (Fama and French, 2015, 2016, 2017, 2018; Hou et al., 2015; Stambaugh and Yuan, 2016; Daniel et al., 2019). However, it is still difficult to explain my predictors constructed by firm partners' information or firm peers' information using popular factors. Therefore, my research is not only a thought-provoking empirical fact with implications for investment strategy, but also has fundamental implications for the construction of new pricing factors.

In addition, I also examine potential mechanisms to explain return predictability. In Chapter 3, I find that mechanisms of the limits to arbitrage, the investors' limited attention, the opaque internal information of the conglomerate, and the information complexity, can explain return predictability along ownership links. In Chapter 4, I find that limits to arbitrage, investors' limited attention, and information complexity can explain return predictability across employee satisfaction-linked firms.

5.1.1 Summary of ownership links and return predictability

In the first chapter, I find subsidiary-parent return predictability and parent-subsidiary return predictability by using a sample of firms from twenty-three developed countries worldwide. In addition, I find a series of new sub-predictors. I find that ownership-linked firms consisting of foreign firms, different industrial firms, minor firms, different name firms, or indirect firms generate a larger predictive power over the future monthly returns of focal firms.

5.1.2 Future research for ownership links and return predictability

Two directions can be investigated in future research. First, I can examine return predictability along ownership links in developing countries. In the thesis, I study the return predictability in twenty-three developed countries. However, although the collection of ownership links and shareholding percentage data of developing countries is very time consuming, it will be interesting to see if return predictability exists in developing countries. This can be developed as a global investment strategy and help us better understand information diffusion in developing countries. Second, I can test bond return predictability along ownership links. Although stock return predictability research is mainstream in the literature, bond return predictability research is becoming increasingly important, since the volume of the US bond market is even larger than the volume of the stock market. Chen et al. (2016) study the bond return predictability in the supply chain. They find that the bond returns of customers can forecast the future bond returns of suppliers, which are similar to the findings of stock return predictability in supply chain (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010). They further find that information along the supply chain travels more gradually in the bond market than the stock market. Therefore, I can examine bond return predictability along ownership links and compare it with stock return predictability along ownership links.

5.1.3 Summary of mechanisms of the return predictability along ownership links

In the second chapter, I examine the mechanisms that can explain and understand return predictabilities along ownership links. In the literature of inter-firm return predictability, a large number of papers use investors' limited attention and limits to arbitrage to explain the return predictability. In this chapter, I use two new mechanisms, the opaque internal information of the conglomerate and the information complexity, to explain the return predictability. My research promotes a deeper understanding of inter-firm return predictability.

5.1.4 Future research for mechanisms of the return predictability along ownership links

In future research, I can conduct more robustness tests by testing these variables in different subsamples and subperiods. In Chapter 3, I test different variables of each mechanism in the global sample. For robustness, I can test these variables in regional samples and/or in two subperiods. It will be interesting to see whether these variables can explain return predictability in regional samples and different periods.

5.1.5 Summary of return predictability in the labor competition network based on employee satisfaction

In this chapter, I find return predictability across employee satisfaction-linked firms by using the Glassdoor firm rankings based on time-varying employees' satisfaction. I find that the returns of employee satisfaction-linked firms can forecast focal firm stock returns. A long-short strategy based on this firm peer predictor yields a monthly Fama and French (2018) six-factor abnormal return of 135 basis points with 1% significance level. This return effect is distinct from industry momentum and a battery of firm characteristics. I find that investors' limited attention, limits to arbitrage, and information complexity may be economic mechanisms to explain the predictive information of employee satisfaction-linked firm peers.

5.1.6 Future research for return predictability in the labor competition network based on employee satisfaction

Although my current employee satisfaction-liked firm peers can forecast the focal firm's stock returns, there could have been some errors in the identification of firm peers using the simple cross-section rolling methods.

Because there is no explicit link between each firm peer and the focal firm, some unconnected firm peers in the predictor portfolio could decrease the predictive effect. To obtain a pronounced firm peer predictor, I could use state-of-art techniques, e.g., machine learning methods, to find accurate employee satisfaction-liked firm peers. I can use the Tibshirani's (1996) least absolute shrinkage and selection operator (LASSO) or Zou and Hastie's (2005) elastic net (E-net) to select the individual firm peer to include in my predictor. Machine learning explicitly identifies the most relevant firm peers for predicting focal firm stock returns. Machine learning is increasingly popular in asset pricing research (e.g., Freyberger et al., 2017; Kozak et al., 2017; Feng et al., 2019; Rapach et al., 2019; Chinco et al., 2019).

5.2 Implication

The importance of the corporate network continues to rise in recent years. In the literature of asset pricing, the majority of predictors and factors are constructed by the firm's own characteristics and information. However, this is just the beginning of the process of exploring and finding predictors and factors designed by firm peer's information and characteristics.

In future research, I can continuously explore new inter-firm linkages and asset return predictability. Current research has found economic links, ownership links, technological links, and strategic alliance links, among others. In future research, I can explore alternative characteristic links, such as advertising links, environmental links, social links, and governance links. In addition, I could not only test stock return predictability along different linkages, but also test the return predictability of other assets, such as bonds, currencies, futures, options, and other derivatives. Finally, I could test the return predictability across different assets. For example, one firm's stock return could predict the other firm's bond return through one specific link.

Appendix – Definitions of main variables

This table briefly defines the main variables used in the empirical analysis of this thesis.

Variable name	Description	Source	Type
$Sub_{i,t-1}$	Parent firm i's ownership-weighted portfolio returns of subsidiaries in month $t-1$	FactSet, CRSP, Eikon	Time-varying updated monthly
$Par_{i,t-1}$	Subsidiary i's control-weighted portfolio returns of parent firms in month $t-1$	FactSet, CRSP, Eikon	Time-varying updated monthly
$ES_{i,t-1}$	weighted portfolio returns of employee satisfaction-linked firms.	Glassdoor, CRSP, Eikon	Time-varying updated monthly
$RET_{i,t}$	Focal firm i's returns in month t denoted in USD	FactSet, CRSP, Eikon	Time-varying updated monthly
$R_{f,t}$	One-month US T-bill rate	Kenneth French Data Library	Time-varying updated monthly

Ln(Size)	Log market capitalization of focal firm in month $t-1$	CRSP, Compustat, Eikon	Time-varying updated monthly
Ln(B/M)	Focal firm's Log book value at the end of December over the market capitalization in month $t-1$	CRSP, Compustat, Eikon	Time-varying updated monthly
Mom	Focal firm's cumulative return from month $t-12$ to month $t-2$	CRSP, Eikon	Time-varying updated monthly
$Reversal$	Focal firm's return in month $t-1$	CRSP, Eikon	Time-varying updated monthly
Turnover	Number of shares traded during a day divided by the number of shares outstanding at the end of the day, averaged over the past 12 months.	CRSP, Eikon	Time-varying updated monthly
Ind_mom	FF48 industry return of focal firm's in month $t-1$.	CRSP, Eikon, FactSet, Kenneth French Data Library	Time-varying updated monthly

AG	Asset growth, defined as year-over-year growth rate of total asset.	CRSP, Compustat, Eikon	Time-varying updated monthly
GP	Gross profitability, defined as revenue minus cost of goods sold scaled by assets.	CRSP, Compustat, Eikon	Time-varying updated monthly
BC	A 0-1 dummy variable that equals one if the focal firm is in the most recent top 100 employee satisfaction firm list and zero otherwise.	Glassdoor	Time-varying updated yearly
MktCap	Market capitalization of the focal firm in the previous month.	CRSP, Compustat	Time-varying updated monthly
Res Inst Own	Residual institutional ownership is the residual from a cross-sectional regression of the percentage of shares held by institutional investors on log market capitalization in month $t-1$.	CRSP, Eikon, Thomson-Reuters Institutional Holdings (13F)	Time-varying updated quarterly

Turnover	Number of shares traded during a day divided by the number of shares outstanding at the end of the day, averaged over the past 12 months.	CRSP, Eikon	Time-varying updated monthly
No. Analyst	Number of analysts of the focal firm in the previous month	CRSP, Eikon, Compustat, I/B/E/S	Time-varying updated monthly
IdioVol	The standard deviation of the residuals from the Fama and French (1993) three-factor model regression of daily stock returns in the previous month	CRSP, Eikon, Compustat, Kenneth French Data Library	Time-varying updated monthly
# Employees	Number of employees of the focal firm in the previous month	CRSP, Eikon, Compustat	Time-varying updated monthly
Analyst earnings forecast	Analyst earnings forecast of the focal firm in the previous month	CRSP, Eikon, Compustat, I/B/E/S	Time-varying updated monthly

Analysts' forecast dispersion	analyst earnings one-year ahead forecast dispersion at the end of the previous month.	CRSP, Eikon, Compustat, I/B/E/S	Time-varying updated monthly
Employees' growth (t)	$The\ number\ of\ employees_{\mathrm{t}} / The\ number\ of\ employees_{\mathrm{t-1}} - 1.$	CRSP, Eikon, Compustat	Time-varying updated yearly
Revenues growth (t)	$\text{Revenues per share}_{\mathrm{t}} / \text{Revenues per share}_{\mathrm{t-1}} - 1.$	CRSP, Eikon, Compustat	Time-varying updated yearly
Profit growth (t)	$(Profit_t - Profit_{t-1}) / average(Assets_t, Assets_{t-1}).$	CRSP, Eikon, Compustat	Time-varying updated yearly

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